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A RELIABILITY MODEL OF AN INVENTORY SYSTEM

by

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CHAPTER 1

INTRODUCTION

Purpose

This study is concerned with inventory errors. As such it is concerned with the type, frequency, and effect of human error on the system output of quantity on hand. The primary function of an inventory system is to supply information for balancing the cost of inventory against the cost of delayed production due to a shortage. One of the primary components necessary is the on-hand quantity. This study will investigate the reliability of this on-hand quantity.

1.1 Problem Origin

This problem was brought to the attention of Drs. D. Grosh and L. Grosh by Mr. Joe Hickey, who was employed by Smith & Loveless of Mission, Kansas, manufacturers of waste treatment equipment. After the annual physical inventory it was found that the firm's records did not match the physical count. Though it is normal to have some discrepancies, management thought they were excessive. The management raised the question of how many errors, and of what size, should one expect under normal circumstances. Mr. Hickey sought the assistance of Dr. D. Grosh and Dr. L. Grosh in answering this question.

Unaware of any investigation into the question of what error should be expected, they suggested that it could be a fruitful topic for a thesis. The purpose of this thesis is to answer that question.

1.2 Problem Description

The problem is to determine the distribution of errors as the difference between the physical and the recorded inventory. The errors with which we are concerned are those that occur randomly over time and are the result of human error.

The problem becomes one of identifying the possible sources of error and quantifying their effects. The goal of this research is to provide answers to what should be expected when a given inventory system is operating correctly. These answers may provide performance standards as well as selection criteria for system design.

1.3 Literature Survey

1.3.1 Inventory Control

There is a great deal of literature available in the inventory control area. This ranges from the design of the documents and the system involved to the mathematical and statistical oriented replenishment models.

In the first case, the system design takes into account procedures to handle every situation that would occur for adding to or subtracting from inventory. In addition, the timing of the component parts of the system and their effect on the accounting functions of the firm are considered. The design of forms, files, and computer systems are considered for handling the information and making it available. But no quantitative study of reliability for the information supplied by the system was found.

In the second case and the more recent areas of study, the various mathematical models, as well as Material Requirements Planning (MRP), use the inventory records as an input to their decision processes. Though some authors, particularly those writing in the MRP area, stress "data integrity", no quantitative study was found. The problem of data accuracy, part of which is the on-hand record, is essential for the successful operation of the inventory decision models discussed in the literature.

1.3.2 Accounting And Business

As in the inventory literature, the accounting and business literature is concerned basically with the timing, costing, and internal control of inventory systems. It is primarily concerned with the accuracy of the valuation of the inventory rather than with the accuracy of the quantity on hand. These two problems are certainly related, although the literature is concerned more with changing costs (making valuation difficult) and fraud than with human error within the system. It appears that before the McKessor and Robbins fraud of the 1930's, certified public accountants did not question the accuracy of a client's inventory records. Since that time, nearly all auditing procedures have contained some physical testing of inventories. However no information concerning a quantitative measure of accuracy regarding inventories was found.

1.3.3 Man Machine Systems

This area was surveyed in an attempt to find an approach to solve the problem. This area of study has dealt primarily with the simulation of time-dependent continuous-type tasks. Examples of this would be a pilot in an aircraft, air traffic controller, or a monitoring task on an assembly line. The type of tasks in an inventory system, counting, recording, keypunching, etc., are not time dependent in the sense of the tasks representative of this area of study. However, the idea of combining several tasks with different reliabilities through a simulation to determine the effect on the system is applicable to the type of problem being investigated.

1.3.4 Human Reliability

1.3.4.1 American Institute For Research Data Store

The American Institute for Research Data Store (15), hereafter AIR Data Store, was developed by Dr. J. W. Altman and others in 1962. The following discussion of the AIR Data Store is almost entirely from a report entitled "Comparative Analysis of Human Reliability Models" by David Meister of the Bunker Ramo Electronic Systems Division (12).

The AIR Data Store is a collection of reliability and time data for various electronic related controls with a few entries pertaining to human communication. The goals of the technique are listed by Meister as follows:

"1) Predict the time and reliability of operator performance.

2) Identify specific design features which degrade operator performance.

3) Provide general guidance concerning selection and training of operators for evaluated equipments."

Some assumptions which are implicit in the method are listed by Meister and will be listed briefly here.

1) Operator performance is influenced by equipment design features.

2) Behavior can be broken down into Stimulus-Organism-Response (SOR) framework where each can be measured and applied independently.

3) The assumption that "interaction effects will tend to balance out so that results will not be consistently in error."

4) Independence between system components.

5) The product rule for determining the system reliability.

There are other assumptions listed by Meister, though these seem to be the ones most important to this study.

The AIR technique is an analytical method for determining the reliability of an operator using a specific piece of equipment. The only goal aligned with the interests of this study is the prediction of the reliability of the operator. In this study we are concerned about reliability of many elements but in addition the effect of the error on the system must be considered. The AIR Data Store may be able to provide some estimates of reliability but can not predict the distribution of errors from the system.

The first assumption seems reasonable though not too applicable to the normal processes found in an inventory system. The functions of counting, transcribing numbers, and keypunching leave few design features available for manipulation. The system design as a whole could be changed but little can be done to change the basic elementary operations in an inventory system.

The second assumption regarding the SOR framework and the independence of elements is questionable. The mediating process would not seem to be independent of the stimulus nor the response. For this reason some objections have been raised regarding the validity of the independence assumption.

The remaining assumptions do not seem to cause a problem with respect to this study. Although the AIR Data Store may be able to provide some reliability data, the analytical framework will not provide the information about the system that is needed for this analysis.

1.3.4.2 Technique For Human Error Rate Prediction

The Technique For Human Error Rate Prediction, or THERP, as it is known in the literature, was developed at Sandia Laboratories in 1961 by Dr. Alan D. Swain and others (21). Mr. Meister points out that THERP, like the AIR Data Store, was strongly influenced by equipment reliability concepts.

The THERP procedure consists of five steps listed by Meister which are reproduced here.

"1) Define the system or subsystem failure which is to be evaluated.

2) Identify and list all the human operations performed and their relationships to system tasks and functions.

3) Predict error rates for each human operation or group of operations.

4) Determine the effect of human errors on the systems.

5) Recommend changes as necessary to reduce the system or subsystem failure rate as a consequence of the estimated effects of the recommended changes."

This approach, says Meister, is quite typical of traditional reliability studies if one substitutes hardware for human.

The goals of this technique are listed by Meister in the aforementioned report. They are:

"1) To derive 'quantitative estimates of the degradation to a man-machine system resulting from human error.'

2) Or, 'to evaluate the human error contribution to systems degradation.'

3) To predict human error rates.

4) To determine those design changes to the system necessitated by the system failure rate."

The goals listed here are for practical purposes identical to the goals of the AIR Data Store. As the following list of assumptions will show, THERP is not as restrictive as the AIR Data Store. Meister calls it "very pragmatic about its assumptions."

1) No assumption of independence is required. It is left to the user or situation.

2) It takes into account various phychological and physiological stresses, training, motivation, and situational factors. These are called Performance Shaping Factors (PSF) and they are very subjective in their application.

3) It accepts as data sources a) operational data b) laboratory studies c) similar operations with available data and d) 'expert' judgement-phychological scaling.

4) "Pragmatism - the acceptability of any method of arriving at any answer which solves a problem - is itself an assumption that must be examined. It must be recognized that this assumption makes it difficult to quarrel with the details of any methodology as long as that methodology appears to 'work.' Since the author's point of view is that the purpose of human reliability predictive models is first to solve system development problems and only secondarily to serve as conceptual tools to explain man-machine behavior, pragmatism is acceptable to him, but only to the extent that it is buttressed as much as possible by detailed clarifying procedures."

Obviously THERP is similar to the AIR Data Store in many of its goals. The comments about the goals of AIR and their applicability to the present study also apply to THERP. However, it is quite obvious that the less restrictive assumptions of THERP allow it to be applied to a much larger set of problems.

The first four steps of the THERP procedure will be taken in this study. The fourth step, to determine the effect of human errors on the system, is essentially the goal of this study. Like the AIR system, THERP measures this effect in terms of probability of failure. This is not sufficient for the present study which requires a distribution of errors.

As with the AIR Data Store, THERP will provide some useful information but the technique will not answer the question of this study.

1.3.4.3 Simulation Approaches

David Meister in "Comparative Analysis of Human Reliability Models" (12), investigates some simulation models for predicting System Reliability. These methods are dynamic rather than static as were the two previous techniques. The static models do not really model a system in the strictest sense, which was one objection to them. A true model would provide us with an error distribution rather than a probability of an error. The Siegel 1-2 Man Model is such a simulation technique.

Without discussing the total Siegel Model, some objections to its use in this situation can be raised. It allows reliability distributions rather than point estimates of reliabilities as did the static techniques.

This indicates that more information is needed regarding the reliabilities of the system components. This human reliability information is not available. The second objection was made in section 1.3.3 regarding time dependent continuous type tasks. This is not the kind of situation being considered and would unnecessarily complicate the model.

The simulation approach will allow a true model to be built providing the error distribution rather than the probability of error. However, as we have seen, the present models require more knowledge of the reliabilities for the human tasks than is available.

1.3.4.4 Predicting Clerical Error

Many of the tasks performed in an inventory system are clerical in nature. In order to answer the questions brought up by this study we need to know what kind of errors are made and how frequently. The AIR Data Store provided some information regarding reliabilities of human operations but more information is needed.

In a paper titled, "Human Transmission of Numbers and Letters", Dr. Stephan Konz et al. (8) investigated the errors made during transmission through four separate experiments. Through the four experiments they concluded that different techniques of transmitting information led to different numbers of errors. Though the number of errors per bit of information can not be used to obtain a reliability, because of time stress induced in the experiments, there are some system design features that can be derived from the experimental results.

One of the variables affecting the number of errors made was whether the information being transmitted was numbers or letters. It was found that more information could be transmitted with fewer errors per bit with letters than with numbers. In addition they found that visual transmission is better than audio and that breaking long messages into shorter parts increases accuracy.

Though using alphabetic characters for manufactures' part numbers might have some disadvantages over using numerical digits, the other two ideas can certainly be used in the design of inventory systems. Generally visual transmission is used in all cases. The idea of breaking messages down is also used though in some cases improvements could be made. The study found that groupings of 3-3-3 and 3-4-2 were better than 4-5, 2-2-2-2-1, and 9. Thus for a nine digit part number some groupings would provide better transmission accuracy than others.

Gary Carlson, of Advanced Information Systems (Los Angeles, California), wrote a paper titled "Predicting Clerical Error" (1). The paper discusses a study done in a bank on check proof machines. These machines are similar to a keypunch. The study investigated the errors made while proofing over 2,000,000 checks. The errors were analyzed in an attempt to develop a model to predict the errors. The most common errors were found to be substitution and omission. As a result, predictive routines were developed that correctly predicted 46% of 4,155 new errors.

Because the above study was done on checks where the quantities are dollars and cents, the errors may not be applicable to a nine digit part number. However, a point estimate of the reliability of a keypunching operation might prove useful in this study.

1.4 Investigative Procedure

The investigative procedure will be described in this section of chapter one. The remaining three chapters will address experimental design, data analysis, and finally conclusions.

The investigation will begin by describing what is felt to be a typical inventory system. The system will be described using "tree diagrams" or "decision trees" in addition to process flow charts. The descriptions will concentrate on human operations which are subject to error. This description will aid in the development of a FORTRAN program to simulate the inventory system.

The FORTRAN simulation will be used to estimate the error variance between the inventory record and the physical count. FORTRAN was chosen over several simulation oriented languages because of its execution speed. This error variance will be tabulated as a histogram with error size and frequency being printed. An attempt to validate the model will then be made by showing that it behaves in a reasonable manner.

The relative importance of the various system parameters will be determined by comparing and contrasting the tabulated histograms. The two methods of analysis to be used are two dimensional marginal contingency tables and linear regression. The contingency tables will be used to identify the important variables. Linear regression takes the place of cross-classified categorical data models to determine the relative importance and interactions of variables. The use of linear regression rather the correct cross-classified categorical data models was suggested by the statistics laboratory at Kansas State University because no programs for the latter were available on campus.

The final chapter will introduce a method of application to the real world using stochastic inequalities such as Techbycheff's inequality. These inequalities will be used to establish bounds or control limits on random inventory error.

CHAPTER 2

EXPERIMENTAL DESIGN

2.1 An Inventory System

It is first necessary to choose an inventory system to model. This system should have all the basic components common to any inventory system while having few unique characteristics. It should be a system which the researcher can easily learn or one that is already familiar. The inventory system described in this chapter meets these criteria.

In analyzing this inventory system different kinds of error will be discussed. To prevent ambiguity, some terms will be defined. The term "error" will indicate an incorrect operation or action. The term "discrepancy" will indicate a difference between the physical inventory and the recorded inventory. Inventory discrepancies are caused by errors.

As in most inventory systems, this system uses a computer to maintain the records. In this study we will assume that the computer has a reliability equal to 1.0. The errors with which we are concerned are those random human errors occurring throughout the system. Only those human errors which will have an effect on the on-hand inventory or the inventory record will be modeled.

The inventory system to be modeled uses a 9 digit part number (P/N) which is grouped according to the pattern 3 digits, 4 digits and 2 digits. According to the paper by Dr. S. Konz (8) this is one of the best groupings of 9 digits for error-free transmission. The system has 13,041 parts in inventory. There are 46,800 receipts per year on the average to maintain the inventory of those 13,041 parts. On the average there are 422,500 production withdrawals from stock each year and an additional 4,000 engineering and production sample withdrawals in a year. The next 3 sections will discuss the 3 types of transactions possible in the inventory system.

2.1.1 Receiving

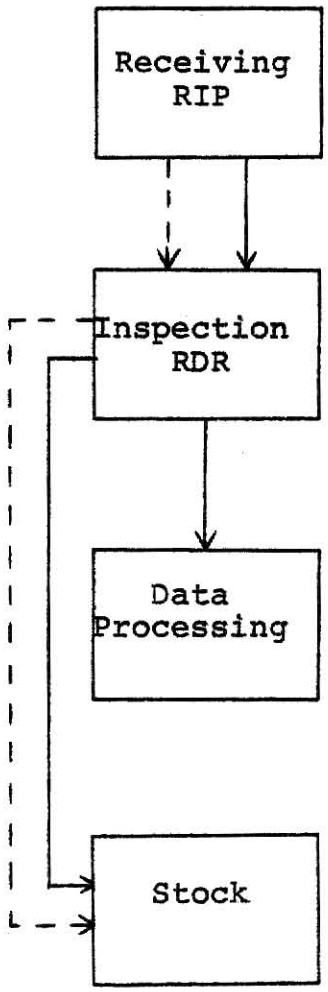
The receiving transaction will be defined to include all the actions necessary to add one order to inventory. The receiving portion of the inventory brings objects from outside the system into inventory in order to maintain some predetermined minimum stock level. A description of what takes place in a receiving transaction follows.

2.1.1.1 Description Of Receiving

Figure 2.1 shows the flow of material and paper in

THIS BOOK CONTAINS NUMEROUS PAGES WITH DIAGRAMS THAT ARE CROOKED COMPARED TO THE REST OF THE INFORMATION ON THE PAGE.

THIS IS AS RECEIVED FROM CUSTOMER.



Enter P/N and purchase order number on RIP (Receipts in Process) report. Verify the quantity on the packing slip.

Complete the RDR (Receipts Disposition Record). Pull the engineering drawing and inspect part. Disposition may be scrap, stock, or returned to supplier, based on inspection results.

A copy of the RDR is keypunched recording part number and quantity to be stocked. When processed, the receipt is removed from RIP.

The receipt is physically moved to the stock room with a copy of the RDR if disposition is to stock. After stocking the RDR is sent to purchasing to match the copy from inspection.

Paper Flow
Material Flow

Figure 2.1 Receiving Flow

the receiving section of the inventory system to be modeled. Upon physically receiving the objects they are entered on the "Receipts In Process" report (hereafter called RIP report). At this time the objects are counted to verify the number recorded on the packing slip. The purpose of the RIP report is to inform interested parties that the objects are physically on location though not in inventory.

The second step in the receiving transaction is inspection. The "Receipt Disposition Record" or RDR is completed. This will have the P/N (part number) transcribed on it as well as the quantity to be entered into inventory. The RDR is a multiple-copy form. The two copies with which we are concerned go, respectively, to Data Processing (DP) and with the objects being processed.

The copy received by DP (Data Processing) will be keypunched in order to transfer the information to the computer. The computer will update the inventory record of the appropriate P/N by the quantity punched. The objects and a copy of the RDR will go to the stock room where the objects in inventory are stored. The objects will then be stored in a predetermined location based on the P/N which is listed on the RDR.

2.1.1.2 Analysis Of Receiving Errors

With the receiving transaction defined one can analyze the possible errors and their effects on the inventory system. The analysis of these errors will proceed by the order of operations in Figure 2.1.

The RIP report is a device for internal communication only. This report does not affect the inventory record in any way. Consequently an error in this report will be of no concern to this study.

Errors made on the RDR may affect the inventory system and must be considered. The RDR has a P/N and a quantity transcribed on it. If either of these are incorrect, it could cause a discrepancy (a difference between the physical inventory and the recorded inventory).

The P/N is normally transcribed from the packing slip to the RDR. However, since this is done in the inspection department where an engineering print is normally used during inspection the P/N could be transcribed from the print. The P/N on the RDR will be used by DP and by the stock room. The P/N may be correct, incorrect valid, or incorrect invalid. As discussed in section 2.1 there are 13,041 parts in the system. If the P/N transcribed is one of the 13,041 it is valid, if not it is invalid. The system will not allow invalid P/N's, thus eliminating one type of error. Figure 2.2 shows a tree diagram of the errors for the receiving transaction. Only the two conditions which affect the system are shown for the transcription operation, correct and incorrect valid.

The quantity must also be transcribed to the RDR. The quantity transcribed is correct or incorrect as shown in Figure 2.2. A later section will discuss the size of the counting error.

The next possibility of error in the receiving transaction occurs in DP. A copy of the RDR is received by DP for keypunching. Both the P/N and the quantity transcribed to the RDR must be keypunched. The possible errors for keypunching are the same as those discussed for transcription. These are shown in Figure 2.2.

The last operation of the receiving transaction occurs in the stock room. The object must be stored in a predetermined location based on the P/N transcribed on the RDR. The objects are either stored in the correct location or in an incorrect location. Again Figure 2.2 shows this last operation. An object stored in the wrong place may be lost to the system in the short term. If one were to go to the correct location for that object and compare the number present with the on-hand record, there would appear to be a discrepancy. However, if a total physical inventory were taken, the objects stored in these wrong locations would be found. Since the purpose of this study is to predict inventory discrepancies as the difference between the physical and recorded inventory, this error will have no effect. The effect of this type of error will be programmed into the model; however, its effect will be nullified by setting the reliability equal to 1.0.

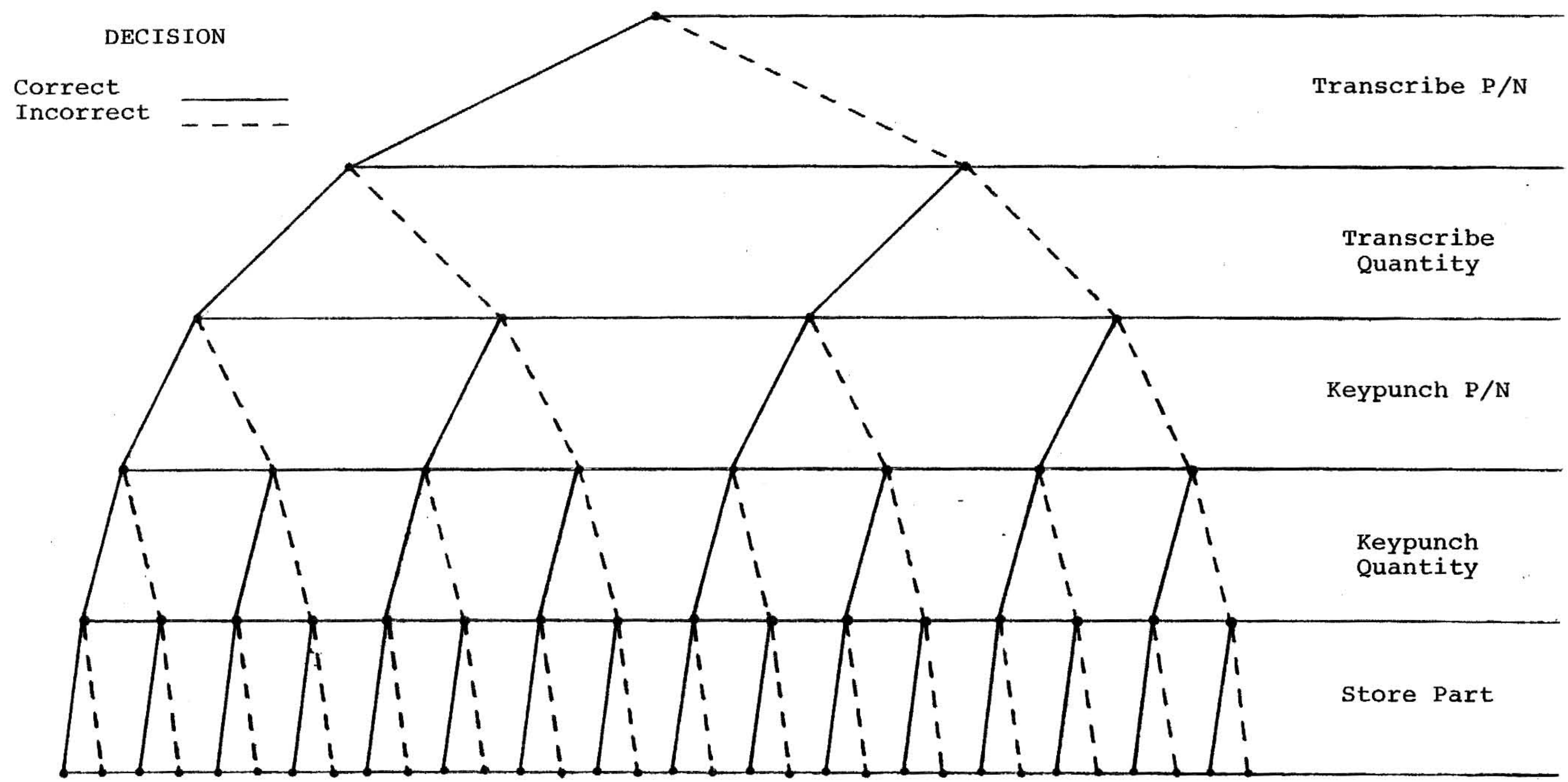


Figure 2.2 Tree Diagram For Receiving

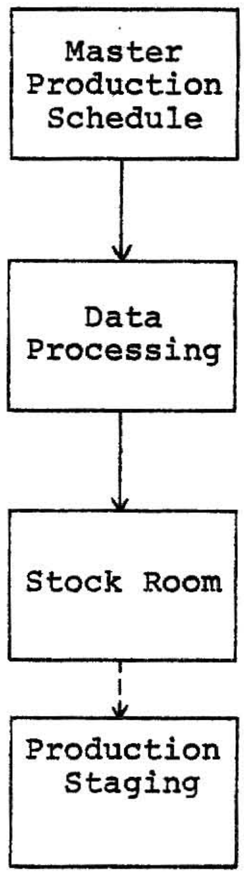
2.1.2 Production

The next phase of the inventory system is the production phase. It is the function of this phase to obtain objects necessary for the production facility without delays. It is through this production transaction that most parts leave inventory. This production transaction is very important because it makes up the largest proportion of transactions. Of the 473,300 total annual transactions approximately 422,500 are production transactions.

2.1.2.1 A Description Of The Production Transaction

The first input for the production phase as shown in Figure 2.3 is the Master Production Schedule. This schedule indicates what and how many to produce. The next step is DP where the Master Production Schedule will be used to generate stock pull requests. Using a Pull Sheet or Bill of Material, DP can produce stock pull requests which can satisfy the Master Production Schedule. These stock pull requests tell the stock room which and how many objects to remove from stock. Data Processing also adjusts the inventory record to reflect the stock pull requests.

These stock pull requests are sent to the stock room where the objects are pulled and then sent to production staging areas. This completes the production transaction.



DP produces pull requests for the production schedule and these are sent to the stock room. The on-hand inventory is then reduced by the appropriate amount.

Pull requests are filled and the parts are sent to the production staging area.

Paper Flow
Material Flow

Figure 2.3 Production Phase Of Inventory System

2.1.2.2 Analysis Of Production Errors

The first possibility of error occurs in the information supplied to DP in the form of Pull Sheets or Bills of Material. These Pull Sheets tell which and how many objects are required for a given item on the Master Production Schedule. An error in quantity or P/N would cause the wrong parts to be sent to the production floor, via the pull requests, every time that item occurred on the Master Production Schedule. This would not, however, cause a discrepancy. It would send the wrong objects to the production floor which would have to be returned by the receiving transaction.

These pull requests are then sent to the stock room where the correct objects in the correct quantities must be pulled. This operation is the critical one. The correct object, that is the one whose number is on the pull request, must be pulled. Next the quantity indicated on the pull request must be counted. If either of these tasks is not done correctly the physical inventory will differ from the inventory record. Figure 2.4 shows the logic tree for the production transaction.

2.1.3 Engineering And Production Samples

This phase of the inventory system is for obtaining objects for uses other than meeting the Master Production

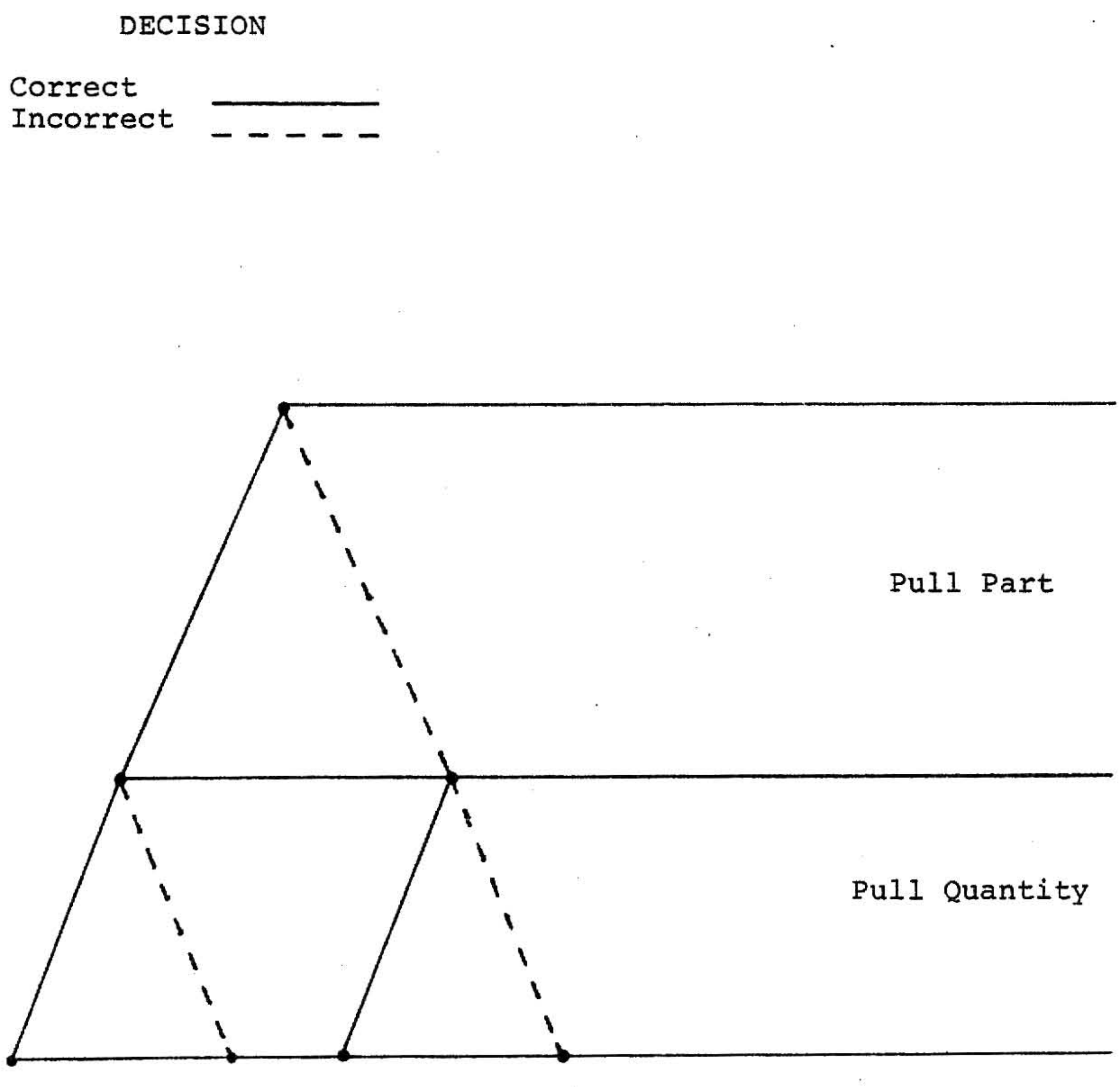


Figure 2.4 Production Phase Tree Diagram

Schedule. This type of transaction accounts for a small percentage of the total transactions.

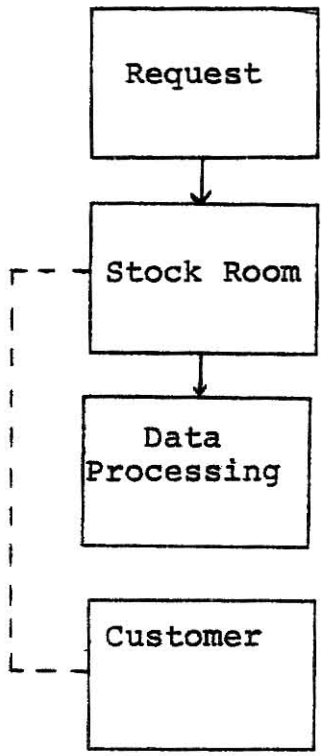
2.1.3.1 Description Of The Sample Phase

This type of transaction begins with a request to the stock room as Figure 2.5 indicates. The stock room attendant will proceed to the appropriate location of the requested object and count out the number required and obtain a bin card. The bin card is a computer card with the P/N prepunched and a marked location for the quantity to be written in. These bin cards are located in front of the bin containing the objects whose P/N corresponds to the P/N punched on the card. The stock room attendant removes one card from the pocket in front of the bin and records the quantity removed from the bin. The card is then placed in a collection box which will then be taken to DP.

Upon receiving the bin cards, DP punches the number recorded on the card onto the card for processing by the computer. The computer will then update the inventory record according to the information on the card.

2.1.3.2 Analysis Of Errors In The Sample Phase

One of the first opportunities for error occurs when the bin card is chosen. If the attendant removes the wrong card, the transaction will carry the wrong P/N causing a discrepancy. Figure 2.6 shows the tree diagram for this phase of the inventory system. The next possibility is that the attendant pulls the wrong object. This would cause a discrepancy because the P/N being adjusted in the records does not correspond to the object removed. Next the objects must be counted and their number recorded on the bin card. An error here would again cause a discrepancy since the record would be adjusted by the wrong amount. Finally the last operation is keypunching. However, it is necessary to punch only the quantity since the P/N was prepunched. A keypunch error, like a counting error, would cause the record to be adjusted by the wrong amount. Figure 2.6 shows the decision points for each operation in this transaction.



The request for a part from stock room attendant is made.

The stock room attendant counts the required parts and records the quantity on the bin card.

The quantity written on the card is keypunched and the inventory is updated.

Paper Flow
Material Flow

Figure 2.5 Engineering And Production Samples

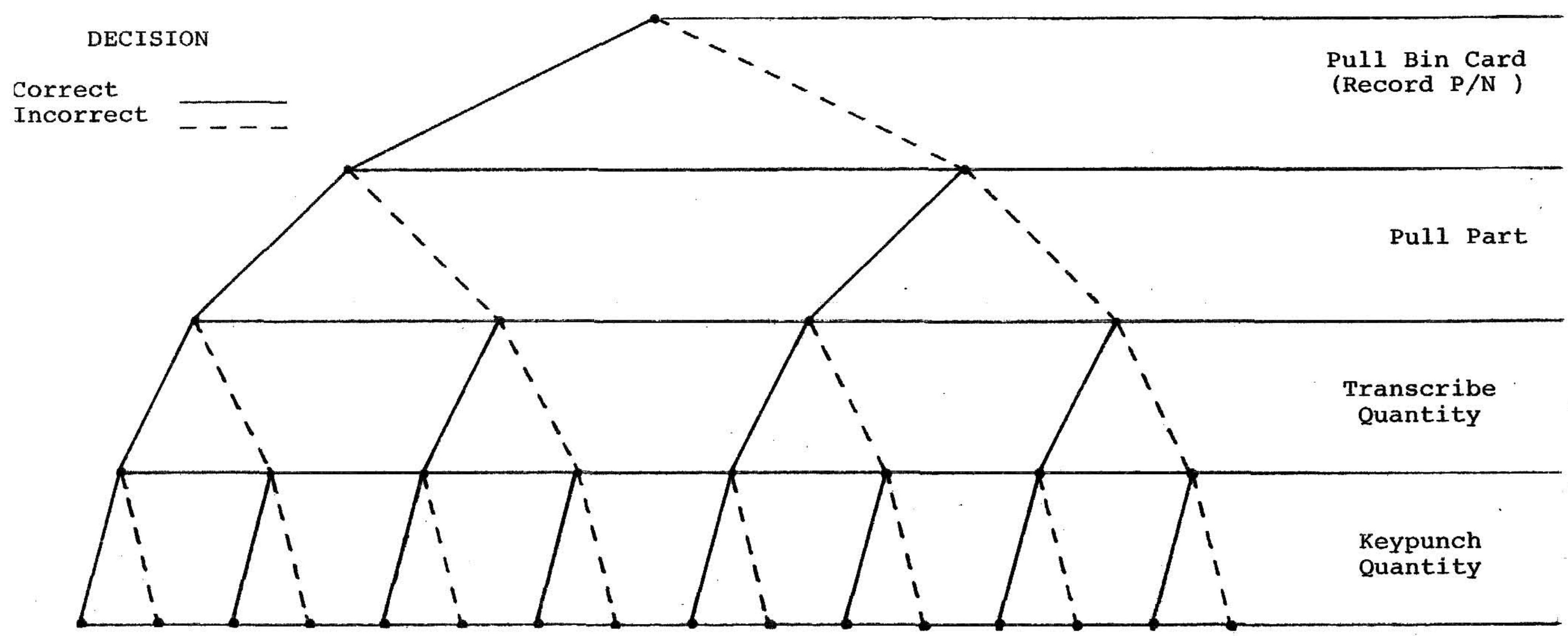


Figure 2.6 Tree Diagram For Engineering And Production Samples

2.2 System Errors

2.2.1 Reliabilities

As indicated in the literature survey section 1.3, there are three sources which provide acceptable reliability estimates. Two of these, the AIR Data Store (15) and the Carlson article "Predicting Clerical Error" (1), prove to be useful in providing reliability estimates.

2.2.1.1 Reliability Estimates From The AIR Data Store

The AIR Data Store analyzes operations using the SOR framework as discussed in section 1.3.4.1. In addition it uses the "product rule" for determining the reliability of an operation. Each reliability estimate required will be broken down into its SOR elements and the product of these will give the AIR estimate of the reliability of the total operation. In some instances each element may be made up of a product itself or combined with another.

Figure 2.7 shows the calculation of the reliability of transcribing a number. This would apply for reading a number of 5-10 digits and writing it down on a form as in a P/N. The first element is the input or stimulus. In this case it would be reading a label with 6-7 digits. This operation is assigned a reliability as indicated of 0.9991. This is then modified by the legibility of the number being read which may be ambigious. This introduces the 0.9997 multiplier. The next consideration is the size of the printing which may be as small as 1/8 of an inch, further modifying the reliability by a factor of 0.9994. The product of these three gives an input reliability of 0.9982. Continuing to the mediating response which is identification recognition we find a value of 0.9997. The output portion is built up in a similar fashion in Figure 2.7. The calculated reliability is shown at the bottom of Figure 2.7.

To apply this reliability to the case of transcribing a P/N it must be further modified to represent only the reliability of what is being modeled. In section 2.1.1.2 it is mentioned that only valid P/N's are accepted. The system will detect errors which result in invalid P/N's. The reliability calculated is 1 minus the probability of transcribing a wrong number. The reliability needed is 1 minus the probability of transcribing a wrong number, that is one of 13,041 valid P/N's. To get this reliability some simple calculations are necessary.

The probability of an error is (1-0.9974). The probability of getting a valid P/N at random with 9 digits is (13,041/999,999,999). The reliability needed is 1 minus the product of the two expressions listed above or 0.999999966. This is the reliability estimate needed for this analysis. From this reliability it is

TRANSCRIBING A NUMBER

Parameter	Description	Parameter Reliability	Element Reliability
Input (Labeling)			
1	Span, 6-7 digits	.9991	
2	Legibility (Potentially Ambigious)	.9997	
3	Size of Printing 1/8"	.9994	.9982
Mediating Response			
2	Identification Recognition	.9997	.9997
Output (Writing)			
2	5-10 digits	.9997	
3	Familiar Message	.9999	
4	Condensed (Writing in one place on one form)	.9999	.9995

Reliability of Transcribing a Number ------------------ .9974

Figure 2.7 AIR Reliability Calculations (Transcribing a Number) apparent that there is a small chance of getting a valid P/N by chance.

The next reliability estimate will be for a counting and recording operation. Figure 2.8 shows the necessary calculations from the Data Store. In this case the input and mediating elements are combined with numerical manipulation. The other calculations are very similar to those discussed in Figure 2.7. Unlike the previous reliability this reliability needs no alteration for use in this study.

2.2.1.2 Keypunch Reliability Estimates

From the reliabilities calculated in section 2.2.1.1 it is evident that a large sample size would be necessary to establish a reliability with much confidence. The lowest reliability estimate was 0.9974 for transcribing a number. In 10,000 trials one would expect only 26 errors. For this reason the reliability estimates for this study must be taken from what is available in the literature.

In an article titled "Predicting Clerical Error" (1) Gary Carlson studies the reliability of check proofing. This operation is similar enough to keypunching P/N's and quantities that a point estimate of the reliability of one would be a reasonable estimate for the other.

COUNTING AND RECORDING

Parameter	Description	Parameter Reliability	Element Reliability
Input and Mediating (Counting)			
1	Numerical Manipulation	.9991	.9991
Output (Writing)			
2	2-5 digits	.9998	
3	Familiar Message	.9999	
4	Condensed (Writing in one place on one form)	.9999	.9996

Reliability of Counting and Recording ------------------ .9987

Figure 2.8 AIR Reliability Calculations
(Counting and Recording)

In listing 2,000,000 checks there were 2,110 errors made. That is only about 1.1 errors for each 1,000 checks. Reliability is 1 minus the probability of error. Therefore the reliability estimate for the check proof machines is as follows.

$$1 - \frac{2,110}{2,000,000} = 0.9989$$

This is the best estimate found for the reliability of keypunching operations.

Like the reliability estimate for transcribing numbers when applied to P/N's, this reliability must also be modified to reflect the valid part numbers only. For keypunching P/N's the reliability would be as follows.

$$1 - (1-.9989)\frac{13,041}{999,999,999} = 0.999999986$$

This reliability reflects the probability of not making an error and not making an error that is a valid P/N.

2.2.2 Counting Errors

In order to determine the effect of errors on the records of the inventory system it is necessary to estimate the size of an error given that an error has occurred. In counting objects one would intuitively expect that the errors made would depend on the number of objects being counted. One would expect very small errors in counting 10 objects but much larger errors in counting 100 or 1,000 objects. In addition, one might expect more small errors than large errors. A distribution which reflects these assumptions is needed.

2.2.2.1 Poisson Distribution

The Poisson distribution with suitably chosen parameters satisfies these intuitive ideas about counting error. Small values have higher probabilities than large values. This would reflect more small errors than large. The size of the errors can be related to the number being counted by making the mean of the Poisson distribution dependent on the quantity to be counted. The only problem with the Poisson is that it could include 0 as an error size. This must be altered by eliminating the probability of a 0 occurrance. This derivation is done in Appendix A.

2.2.2.2 Other Counting Error Distributions

The intuitive ideas about error pointed toward the Poisson distribution. These ideas may or may not be accurate.

Therefore to determine the affect of these assumptions on the study, other distributions should be tried which do not reflect the previous assumptions. Two other simple distributions, a uniform and a triangular, will be used to test the sensitivity of these assumptions. The means of these distributions will all be maintained the same.

2.2.2.3 Keypunch Errors

Just as the size of counting errors must be determined so must the size of keypunch errors be determined. The probability of a keypunch error was estimated from the Carlson article "Predicting Clerical Error" (1). However, no determination of how to predict the size of an error was discussed.

Carlson found that the most common check proof errors were substitution, omission, and insertion in order of decreasing occurrence. Other less frequent errors were double omission, double substitution, transposition and double insertion. Carlson analyzed 2,110 errors made on 2,000,000 checks listed to develop routines to predict error. The routines were then used to predict 4,155 new errors on over 4,000,000 new checks. The predictive routines successfully predicted 46% of these errors.

These predictive routines were developed for expressions of dollars where a decimal is required. The routines necessary to predict the errors made while keypunching integer numbers for quantities are not available. The time necessary to construct these routines and test them would be prohibitive in this study. Therefore the distributions of counting error will be used for keypunching error. These will be altered to investigate their effects concurrently with the counting error distribution. This enables the use of one routine for both counting error and keypunching error.

2.3 Design Of The Simulation

The simulation is relatively simple since the activities are not time dependent. Since it would require a large program and a great deal of time to simulate over 13,000 objects simultaneously, only one object will be simulated at a time. This implies that an error in one object will not affect another. That is an error made while working with a given part may cause a discrepancy with that part but will not cause a discrepancy with a different part.

A double discrepancy (two discrepancies for one error) would normally occur if a P/N error occurred. A

P/N error would adjust the inventory of the wrong object which would cause two discrepancies in the system. One discrepancy occurred in not adjusting the record of the correct object. The other discrepancy occurred when the record of the incorrect object was adjusted. To see how this might affect the results an analysis of each case where a P/N error could occur will be made.

The first case for a P/N error occurs in the receiving section as discussed in section 2.1.1.2. There are two opportunities for this error, one in transcribing the P/N and one in keypunching the P/N. The reliability estimates for these two operations are respectively 0.999999966 (2.2.1.1) and 0.999999986 (2.2.1.2). Since these reliabilities are so extremely high it is the opnion of the researcher that the lack of interaction will not have any significant effect on the results.

The next possibility for a P/N error occurs in the production phase when filling pull requests. This type of error is discussed in section 2.1.2.2. If the wrong part is pulled for production, the production or quality control sections would find the error. The parts would then be returned for the correct part and the system would be corrected. For practical purposes the reliability of this operation can be assumed equal to 1.0. Therefore the problem will not occur in this phase of the inventory system.

The last place an error of this type might occur is in the engineering and production sample phase discussed in section 2.1.3.2. The error can occur by choosing the incorrect object or by choosing the incorrect bin card. For the reasons mentioned previously the reliability of choosing the correct object is assumed to be 1.0. The problem of choosing the incorrect bin card is not a problem due to the relative numbers of transactions and the size of the transactions. From section 2.1 note that there are on the average 473,300 transactions of all types each year but only 4,000 are engineering and production samples. That is, less than 0.8% are engineering and production samples. In addition to the small number of transactions the maximum quantity of an engineering and production sample transaction is small. For these reasons the researcher does not believe that the limitation of simulating one part at a time will have a significant effect on the results.

The remainder of section 2.3 will discuss the major components of the simulation. A program listing is shown in Appendix B.

2.3.1 The Analysis Of Decision Trees

This section will discuss the use of decision trees in the simulation of the inventory system. Each of the three inventory phases has a decision tree describing possible outcomes or paths that might be taken. At the end of each path the appropriate action to be taken on the physical and on-hand inventory records is indicated.

Based on the probabilities and a random number stream the appropriate paths of the decision tree will be followed. At the end of each transaction adjustments to the numbers representing the physical and the inventory record can be made.

2.3.1.1 The Receiving Decision Tree

Figure 2.9 shows the decision tree for the receiving phase of the inventory system. The comments on the right hand side indicate what operation is occurring at that level of the tree. The two bottom rows of letters indicate the effect on the system parameter at the right. The "C" indicates a correct adjustment. The two errors shown are indicated by "I" and "NC" which represent an incorrect adjustment and no adjustment respectively.

Proceeding down the left side of the tree the first branch along the bottom represents no errors. Both the inventory record and the physical inventory were correctly adjusted. The next branch to the right indicates an error in storing an object. This had no effect on the inventory record which was properly adjusted. However, since the part was stored in the wrong location there was no change to the number of objects at the correct location. The next branch represents an error in keypunching a quantity. This will cause the inventory record for that object to be incorrect. Since the part is stored in the correct location the physical quantity is adjusted correctly. In fact it should be recognized that the only error which will affect the physical record is storing the object in the wrong location. Since this is constant throughout it will not be discussed for the remaining branches. The fourth branch, like the third, adjusts the inventory record by the wrong amount due to the keypunch errors. The fifth and sixth branches have a quantity transcription error which again incorrectly adjusts the inventory record. At the seventh and eighth branches errors in recording and keypunching occur which again incorrectly adjusts the inventory record. An assumption involved here is that the keypunch error does not correct the recording error. This would certainly be the most likely situation. However, one error could correct the other in this situation and the program reflects this by calculating an error for each situation. Thus it is possible to have a correct adjustment to the inventory record both in the actual system and in the simulation.

Branches nine through twelve show missing decision points at two or more levels. Branches nine and ten have an error in keypunching the P/N. Remembering that only one object is simulated at a time no quantity adjustment can be made. Therefore it is not necessary to look at decisions regarding the quantity parameter. This also holds true for branches eleven and twelve. It is possible to condense these four branches into two because the outcome of branches nine and eleven is identical to the outcome of branches ten and twelve.

This decision tree is represented by several logical if statements in the simulation. Each time a receiving transaction occurs this decision tree is followed. At the end of each transaction the inventory records are adjusted to reflect the simulated errors that occurred in processing that transaction.

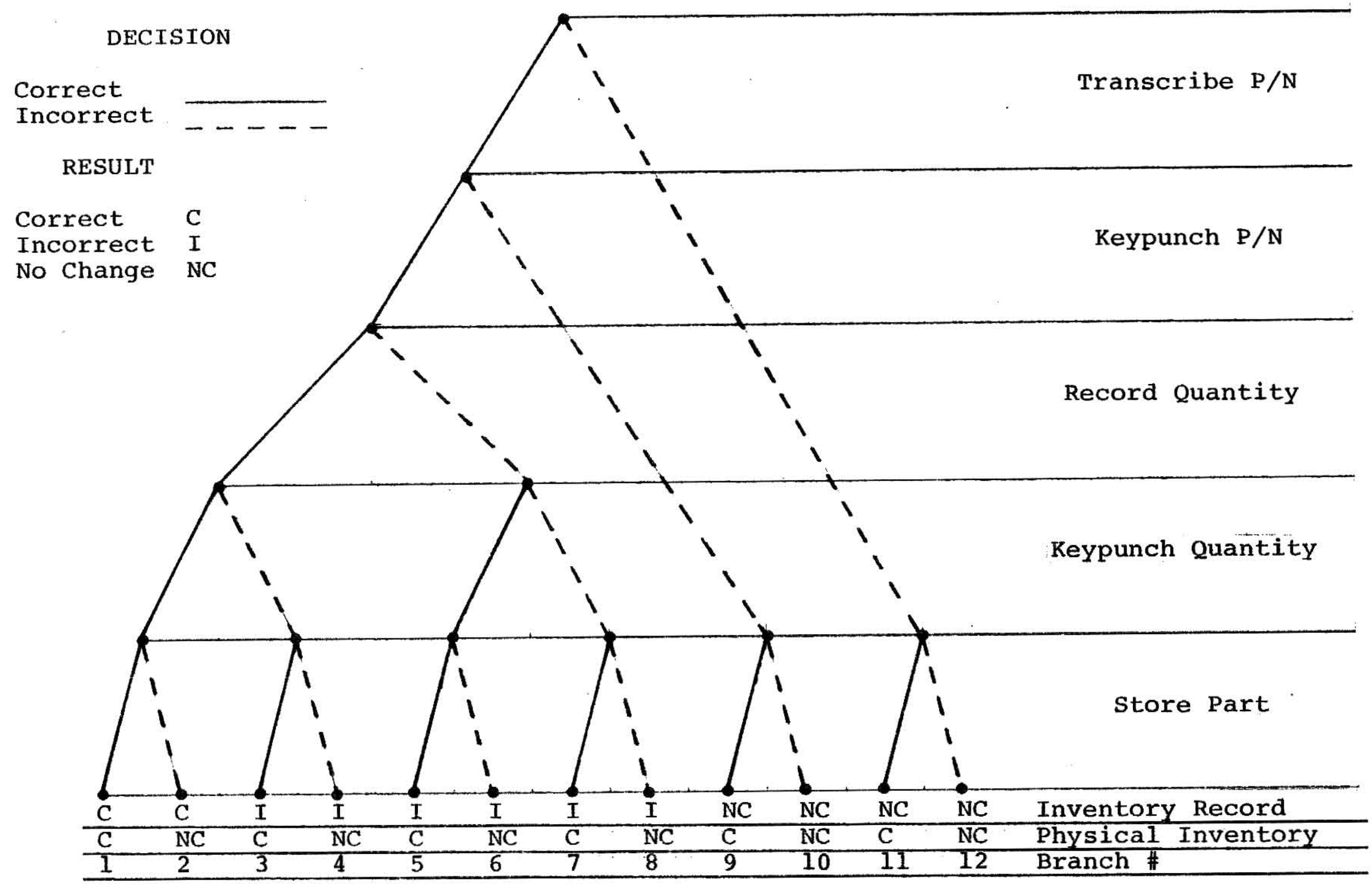


Figure 2.9 Receiving Decision Tree

2.3.1.2 The Production Decision Tree

The next phase of the inventory system is the production phase. Figure 2.10 shows the decision tree and the effect on the object being simulated. A review of section 2.1.2.2 may be helpful in understanding this section.

Branch one represents no errors and both the inventory record and the physical inventory are correctly adjusted. In addition the inventory record will always be adjusted properly in this type of transaction since it is done by the computer when generating the pull requests. The only record which can be incorrect is the physical inventory. Branch two represents an error in pulling the quantity, that is, miscounting. This will cause the physical inventory to be incorrect. Branches three and four have identical effects on the inventory record and the physical inventory. If an error is made in pulling a part, the physical inventory of the correct part will not change. Since only the correct part is being simulated the quantity adjustment has no effect, there being no record to adjust. This completes the decision tree for the production phase.

2.3.1.3 Engineering And Production Samples

The engineering and production sample phase of the inventory system discussed in section 2.1.3.2 is the last

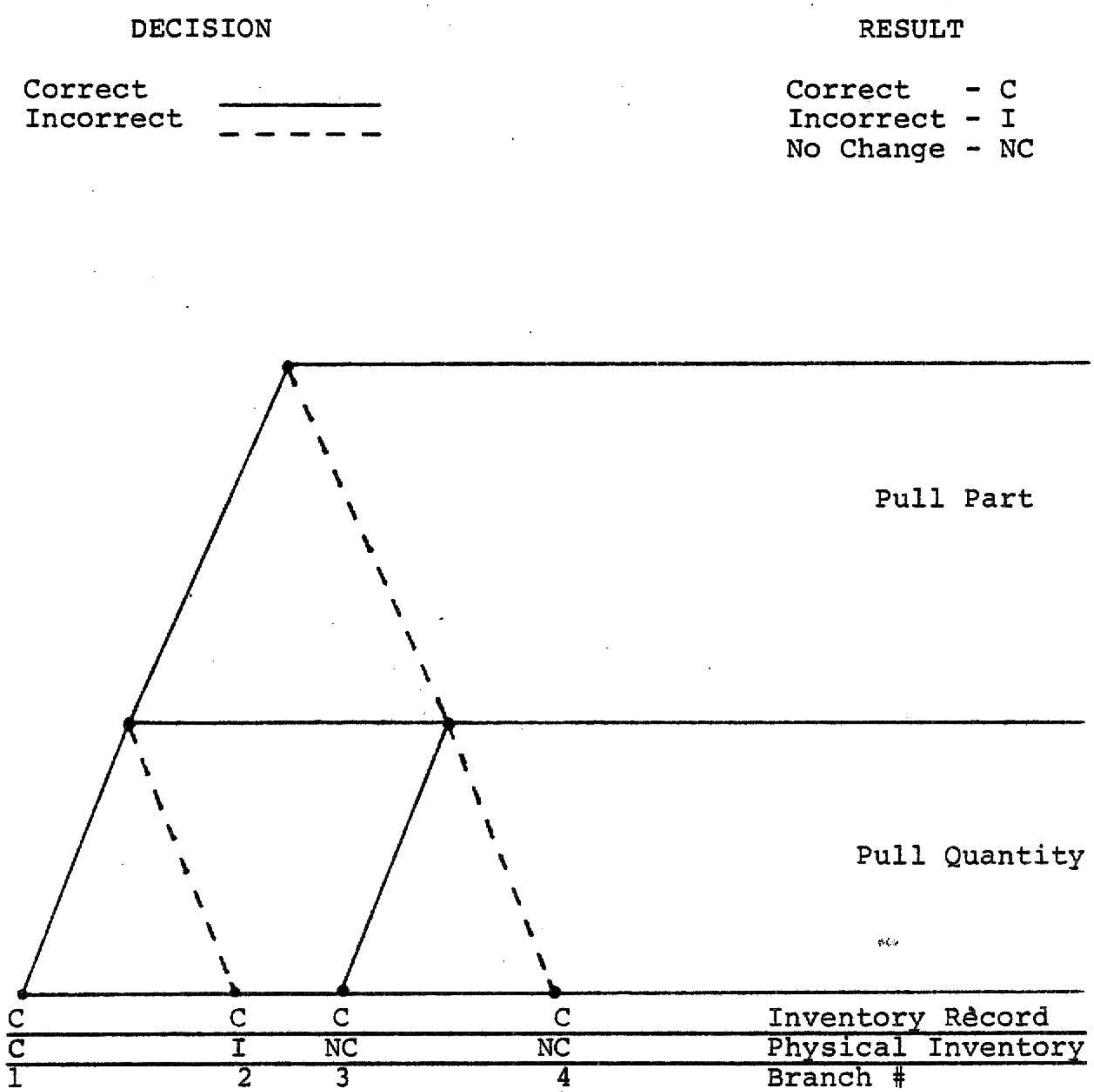


Figure 2.10 Production Decision Tree

phase of the inventory system to discuss. Figure 2.11 shows the decision tree for this phase of the system which was previously discussed in section 2.1.3.2.

The first branch represents no errors in the system and both the physcial inventory and the inventory record are correctly adjusted. Branch two represents a keypunch error in the quantity carrying an incorrect adjustment to the inventory record. The physical inventory is correct. Branches three and four represent a transcription error on quantity causing the inventory records to be incorrectly adjusted while the physical inventory is correct. Branch four which also has a keypunch error could cause a correct adjustment if the transcription error and keypunch error cancelled one another. Branches five through eight have an error in pulling (choosing) a part. That is, the wrong part was withdrawn, causing no change to take place to the physical inventory of the simulated part. While branch five correctly adjusts the inventory record, branch six has a keypunch error in quantity causing an incorrect adjustment to the inventory record. Like branch six, branches seven and eight have quantity errors which cause incorrect adjustment of the inventory record. Branch eight, like branch four, has the possibility of off-setting errors.

Branches nine through sixteen all represent errors in pulling the bin card, causing the incorrect P/N to be recorded. In each case no adjustment is made to the inventory record of the part being simulated. Branches nine through twelve have no errors in choosing the correct part; consequently, the physical inventory is correctly adjusted. Branches thirteen through sixteen represent errors in pulling the part. This error causes no adjustment to the physical inventory of the part being simulated. This concludes the decision tree analysis of the sample phase of the inventory system. This is the vehicle for simulating this phase of the inventory system and making decisions about what adjustments are appropriate.

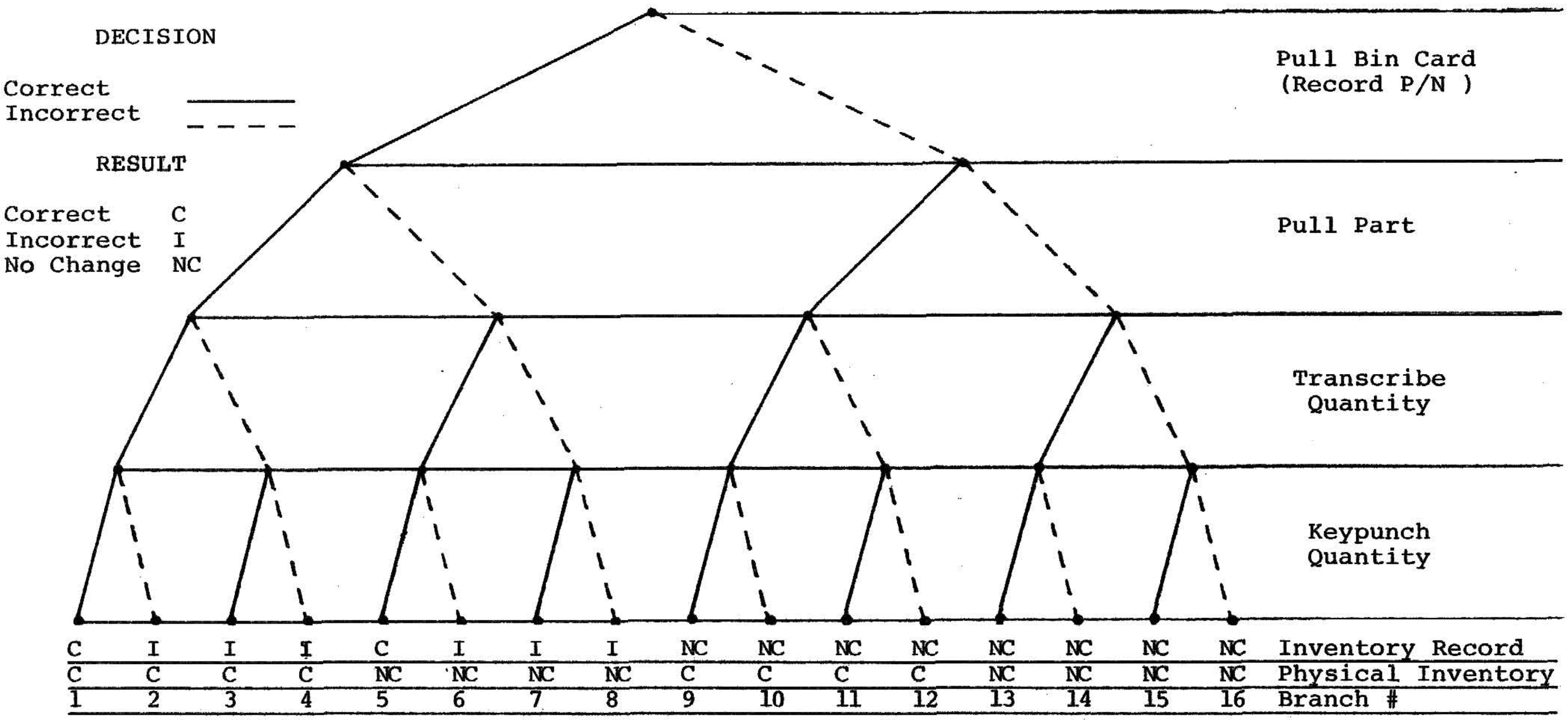


Figure 2.11 Engineering And Production Sample Decision Tree

2.3.2 Control Of The Simulation

This simulation is controlled by the total number of transactions processed and the number of parts simulated. Each simulation run will simulate several parts independently to create a distribution of discrepancies with the given system parameters. The concept is to represent a total inventory by simulating one part several times and observing the discrepancy distribution. The "discrepancy distribution" is defined as the group of differences between the physical inventory and the recorded inventory. These differences are calculated by subracting the recorded inventory from the physical inventory.

The simulation is controlled by nested loops. The outside loop is the number of parts to be simulated. When the indicated number of parts have been simulated, the simulation transfers control to a data analysis section which will print the statistics of the current simulation.

The next loop is the total number of transactions indicated. A receipt is one transaction, as is a production pull and an engineering and production sample. The total numbers of these present indicate the total activity for a part. When the required number of transactions have been simulated the data concerning the part is stored and a new part is simulated if the first loop is not complete..

For a given part the relative numbers of transactions are controlled just as an inventory might be controlled. The inventory on hand is always maintained and receipts are made whenever the on hand quantity falls below a given level. A constant number of engineering and production samples are required for each part. This completes the macro-control of the simulation.

At the micro-level the decision trees discussed in section 2.3.1 are followed by assigning probabilities to each level and then choosing a random number. Based upon the random number and the reliability, the path down the tree is indicated. This is commonly called a Monte Carlo simulation. The random number generator used is the McGill random number package "Super-Duper" (10).

This random number generator combines a multiplicative congruential generator and a shift register generator. The multiplicative generator uses a multiplier of 69069 and the shift register is on 32 bits (right shift 15, left shift 17). The two are added as binary vectors producing a sequence with a period of approximately 5×10^{18}. This generator is very fast and produces a good pseudo-random number stream.

2.3.3 Output Of The Simulation

The output of the simulation consists of the input parameters, some statistics and a table (discrepancy distribution) showing the result of each part simulated.

The input parameters required are the total number of parts to simulate, transactions per part, reliabilities for all branches of the trees in section 2.3.1, maximum and minimum order quantities for each phase, parameters for the error distributions and the starting random number seeds. These input parameters are printed to identify the results of the simulation.

The output from the simulation is a table of error size and frequency called a discrepancy distribution. Calculations are done to indicate the percent of the total parts simulated that have a discrepancy of a given size. In addition, the first four moments of the discrepancy distribution are calculated. This provides all the information for further data analysis of the simulation.

2.4 Simulation Experiments

The objective of the experiments is to obtain information about how various assumptions and input parameters affect the discrepancy distribution. An analysis of the discrepancy distributions will indicate which assumptions and parameters are important in the simulation.

2.4.1 The Counting Error Distributions

As discussed in section 2.2.2 the Poisson distribution seems to represent adequately the intuitive ideas about counting errors. Since there is no experimental evidence to support this assumption, it is necessary to evaluate the importance of the counting error distribution. This can be done by comparing the results of models using the Poisson distribution with models using the uniform or triangular distribution for a counting error distribution. A comparative analysis of the discrepancy distributions from the respective simulations will indicate the importance of the choice of error distribution. The inputs for either purchase order quantity or production order quantity consists of the maximum and minimum values. The mean is half way between these input values. The Poisson counting error distribution has a mean approximately equal to λ times the quantity to be counted. To compare the three distributions (Poisson, uniform, and triangular) the means should be chosen equal so that curve shape is all that changes. These will be the first three experiments run. As indicated earlier an analysis of these experiments will indicate the importance of the counting error distribution. The analysis of these experiments is in section 3.1.1.

2.4.2 Inventory System Parameters

The inventory system parameters consist of those parameters which describe this particular inventory system given the structure described in section 2.1. These parameters are common to each phase, receiving, production, and engineering and production samples of the inventory system.

The input system parameters consist of maximum and minimum quantities, the multiplier for the mean error, and the number of transactions per part. The order quantities are random normal deviates with mean midway between the maximum and minimum and standard deviation equal to one sixth the range. The product of the multiplier for the pseudo mean error (pseudo because of the altered Poisson distribution) and the mean quantity is the pseudo mean error, hereafter called simply mean error. From the input parameters and the above information one can calculate the mean, standard deviation, and the mean error for each phase. These values are of more concern in the analysis than the input parameters alone.

By systematically altering these values one can investigate the effects of each parameter on the inventory system. Each phase of the inventory system will be altered independently of the others. Table 2.1 lists the variables

TABLE 2.1

GLOSSARY OF VARIABLES

R1	-	Reliability number 1	-	Keypunching a quantity
R2	-	Reliability number 2	-	Keypunch a P/N
R3	-	Reliability number 3	-	Transcribing a quantity
R4	-	Reliability number 4	-	Counting a quantity
R5	-	Reliability number 5	-	Counting and recording a quantity
R6	-	Reliability number 6	-	Transcribing a P/N
R7	-	Reliability number 7	-	Pulling a bin card
T	-	Transactions per part		
λr	-	Multiplier for pseudo Poisson error distribution in receiving		
$\bar{X}_{qr}$	-	Mean quantity for receiving		
σ_{qr}	-	Standard deviation of receiving quantity		
$\bar{X}_{er}$	-	Mean error in receiving		
MAX_r	-	Maximum quantity in receiving		
MIN_r	-	Minimum quantity in receiving		
λp	-	Multiplier for pseudo Poisson error distribution in production		
$\bar{X}_{qp}$	-	Mean quantity for production		
σ_{qp}	-	Standard deviation of production quantity		
$\bar{X}_{ep}$	-	Mean error in production		
MAX_p	-	Maximum quantity in production		
MIN_p	-	Minimum quantity in production		

and their corresponding symbols which will be used in the remaining sections of this thesis.

2.4.2.1 Receiving Parameters

In the receiving phase experiments will be conducted to determine the effects of the parameters discussed above on the system outputs. Experiments 4 through 11 are designed to investigate the receiving phase. Each of these experiments have the same parameters in the production and engineering and production sample phase, in addition to having all reliabilities constant. Table 2.2 shows the input parameters in addition to some other parameters for the receiving experiments. For the purpose of analysis the mean quantity ($\overline{X}_{qr}$), quantity standard deviation (σ_{qr}), and the mean error ($\overline{X}_{er}$) are of primary concern. These are a direct result of the input parameters and the following discussion will use these in referring to the experiments.

There are three basic variables to investigate. These are $\overline{X}_{qr}$, σ_{qr}, and $\overline{X}_{er}$. Experiments 4, 9, and 10 let $\overline{X}_{er}$ vary while $\overline{X}_{qr}$ and σ_{qr} remain constant. This will allow an analysis of the effects of varying $\overline{X}_{er}$. Experiments 4 and 5 form one group with $\overline{X}_{er}$ and $\overline{X}_{qr}$ constant while experiments 6, 7, 8, and 11 form another. These will be used to determine the effects of varying σ_{qr} on the system. Finally the effects of varying $\bar{X}_{qr}$, the mean quantity, will be investigated using experiments 6 and 10.

2.4.2.2 Production Parameters

Just as in the receiving phase, there are three basic variables to investigate $\bar{X}_{qp}$, σ_{qp}, and $\bar{X}_{ep}$. Experiments 15 through 22 allow only production parameters to vary. Table 2.3 shows the experiments and their respective input parameters. The following pairs of experiments will be used to investigate the effects of varying $\bar{X}_{ep}$; 15 and 19, 16 and 20, 17 and 21, 18 and 22. Experiments 18 and 19 will be used to investigate the effects varying $\bar{X}_{qp}$ on the output while the following pairs of experiments will provide information on varying σ_{qp}; 15 and 16, 17 and 18, 19 and 20, 21 and 22. In addition there are two other experiments, 4 and 14, which can be used to investigate varying σ_{qp}. These are grouped separately because their purchasing parameters do not match those of experiments 15 through 22.

2.4.2.3 Other System Parameters

No discussion has been given on experiments for the three basic parameters in the engineering and production phase nor on the effect of the number of transactions per part. This section will address these problems.

TABLE 2.2

Receiving Parameters

Exp #	Max_r	Min_r	λ	T	$\bar{X}_{qr}$	σ_{qr}	$\bar{X}_{er}$
4	300	100	.02	200	200	33.33	4.0
5	250	150	.02	200	200	16.67	4.0
6	500	300	.02	200	400	33.33	8.0
7	600	200	.02	200	400	66.67	8.0
8	440	360	.02	200	400	13.33	8.0
9	300	100	.01	200	200	33.33	2.0
10	300	100	.04	200	200	33.33	8.0
11	400	400	.02	200	400	0.00	8.0

TABLE 2.3

Production Parameters

Exp #	Max_p	Min_p	λ	T	$\bar{X}_{qp}$	σ_{qp}	$\bar{X}_{ep}$
4	110	10	.02	200	60	16.67	1.2
14	85	35	.02	200	60	8.33	1.2
15	112	28	.02	200	70	14.00	1.4
16	91	49	.02	200	70	7.00	1.4
17	224	56	.02	200	140	28.00	2.8
18	182	98	.02	200	140	14.00	2.8
19	112	28	.04	200	70	14.00	2.8
20	91	49	.04	200	70	7.00	2.8
21	224	56	.04	200	140	28.00	5.6
22	182	98	.04	200	140	14.00	5.6

As discussed in section 2.3 there are relatively few engineering and production sample transactions and each is for relatively small quantities. For these reasons the effect of this type of transaction is small and thus the effect of the parameters in this phase will also be small. No experiments investigating this phase will be run.

As for , T, the number of transactions per part, experiments 4, 12, and 13 hold all parameters constant except T. Experiments 4, 12, and 13 have respectively 200, 100, and 50 transactions per part. These experiments will be used to determine the effect of T.

This completes the list of experiments involving the system parameters. Next an investigation into the reliabilities must be planned.

2.4.3 Experiments Involving Reliabilities

There are seven basic reliabilities in this simulation. Each reliability may occur several times within the simulation. The reliabilities will be altered by type so each experiment may show several changes. The reliabilities and their corresponding symbols are listed in Table 2.1

R1 and R2 originate from the Gary Carlson article and R2 is then altered because of the system design as discussed in section 2.2.1.2. R3 through R6 originate from the AIR Data Store. R3 and R6 have the reliability calculated as the value for transcribing a number. R4 and R5 use the AIR estimate of the reliability of counting and recording. R4 was increased by an arbitrary amount because no recording is required. The last reliability, R7, is the reliability of pulling the correct bin card in the engineering and production phase. No information is available for calculating a reliability for this operation. A value of 0.999 will be assigned to R7. This value is in the same range as the other reliabilities. As mentioned before, this is not in a significant portion of the simulation.

Table 2.3 shows the experiments designed to investigate the reliabilities. Experiment number 4 will be used as a base case with which each can be compared.

Experiments 4, 25, and 26 will show an investigation of the effects of varying R4. Experiment number 26 shows an increase in the probability of counting error by 10%. The value of R4 in experiment 25 is 1.0 and represents a decrease in the probability of error. Experiments 4, 27, and 28 show changes only in R5. These will be used in the analysis to investigate the effects of varying R5.

Experiments 4, 29, and 30 will be used to investigate the effects of inventory size on the number of errors.

This can be explained by the fact that only valid P/N's are allowed. If there are more valid P/N's and the total possible numbers remains constant, there is an increased probability of error. Since R2 and R6, which deal with P/N error, were altered by the ratio of valid P/N's to total possible numbers they will both change as inventory size varies. Experiment 30 represents a 10 fold increase in inventory size while number 29 represents a decrease in inventory size. Experiments 4, 31, and 32 show a change in R1 and R2. R1 and R2 are based on the estimated keypunch reliability. R1, however, represents keypunching a quantity while R2 represents keypunching a P/N and is of course altered by the ratio of valid P/N's to total possible numbers. These experiments then represent a change in the keypunching reliability while the inventory size remained constant. R7 is now altered in experiments 33 and 34 for comparison with experiment 4. The remaining reliability, R3, is then altered in experiments 35 and 36. The analysis of these experiments will be done in section 3.0.

TABLE 2.4

Reliabilities

Exp #	Reliability # R1	R2	R3	R4	R5	R6	R7
25	0.9989000	0.9999999	0.9974000	1.0000000	0.9987000	0.9999999	0.9990000
26	0.9989000	0.9999999	0.9974000	0.9989000	0.9987000	0.9999999	0.9990000
27	0.9989000	0.9999999	0.9974000	0.9990000	1.0000000	0.9999999	0.9990000
28	0.9989000	0.9999999	0.9974000	0.9990000	0.9984000	0.9999999	0.9990000
29	0.9989000	1.0000000	0.9974000	0.9990000	0.9987000	1.0000000	0.9990000
30	0.9989000	0.9998696	0.9974000	0.9990000	0.9987000	0.9998699	0.9990000
31	1.0000000	1.0000000	0.9974000	0.9990000	0.9987000	0.9999999	0.9990000
32	0.9987000	0.9999999	0.9974000	0.9990000	0.9987000	0.9999999	0.9990000
33	0.9989000	0.9999999	0.9974000	0.9990000	0.9987000	0.9999999	1.0000000
34	0.9989000	0.9999999	0.9974000	0.9990000	0.9987000	0.9999999	0.9949999
35	0.9989000	0.9999999	1.0000000	0.9990000	0.9987000	1.0000000	0.9990000
36	0.9989000	0.9999999	0.9969000	0.9990000	0.9987000	0.9999869	0.9990000
4	0.9989000	0.9999999	0.9974000	0.9990000	0.9987000	0.9999999	0.9990000

CHAPTER 3

ANALYSIS

3.0 Introduction

The experiments described in section 2.4 will be analyzed in this chapter. The data from the experiments will be analyzed using two different procedures. The first procedure will use chi-square contingency tables to compare individual experiments in groups. The second procedure will use the sums of squares analysis from a multiple stepwise regression procedure to compare all parameters across all experiments.

3.1 Chi-Square Contingency Analysis

3.1.1 Counting Error Distributions

Table C-1 in Appendix C shows the contingency table comparing experiments 1, 2, and 3. The chi-square value for this table is 55.76 and there are 36 degrees of freedom. The null hypothesis that all three distributions are the same can be accepted at the 1% significance level where the tabled value of chi-square with 36 degrees of freedom is 58.58 (linear interpolation). However, the null hypothesis can be rejected at the 5% level. This might indicate that the counting error distribution has some moderate effect on the discrepancy distribution. However, this is inconclusive based upon the results of experiments 1, 2, and 3. It should be noted that the curve shapes of the three counting error distributions, Poisson, uniform, and triangular are considerably different. If the comparison were done with counting error distributions more like the Poisson in shape, it might prove very difficult to reject a hypothesis that the discrepancy distributions from the simulation are the same. The remainder of the experiments will use the Poisson distribution for errors.

3.1.2 Inventory System Parameters

The inventory system parameters are the mean order quantities, standard deviation of order quantities, mean error, and the number of transactions per part or the activity level. The next four sections will analyze the experiments in terms of these parameters.

3.1.2.1 Activity Level

The activity level is controlled in the simulation by the number of transactions simulated for each part (T). In an actual inventory system there would be a wide variation in activity levels among the parts in the system. Experiments 4, 12, and 13 each have different activity levels allowing a comparison of the discrepancy distributions as activity levels varies. The number of transactions per part, T, for experiments 4, 12, and 13 are respectively 200, 100, and 50. Table C-2 shows the calculated chi-square value of 366.27 with 26 degrees of freedom while $X^2_{.01}(26)$ equals 45.6. Therefore the null hypothesis is easily rejected at the 1% significance level. There is a significant difference in the discrepancy distributions where activity levels change.

The three discrepancy distributions would be expected to be different since the opportunity for error is directly related to the activity level. One would expect to find more errors and consequently more discrepancies in parts where many transactions took place than in those where fewer transactions took place. The discrepancy size and frequency, as a percent of the total, can be used to illustrate this.

Figure 3.1 shows the ogive for experiments 4, 12, and 13. This is a smoothed curve of cumulative frequency (as a percent of the total) plotted against the absolute value of the discrepancy.

In the lower portion of the graph, below 98%, the curves shift to the right as the transactions per part increase. This indicates that for a given percent of total parts the discrepancy will increase as the number

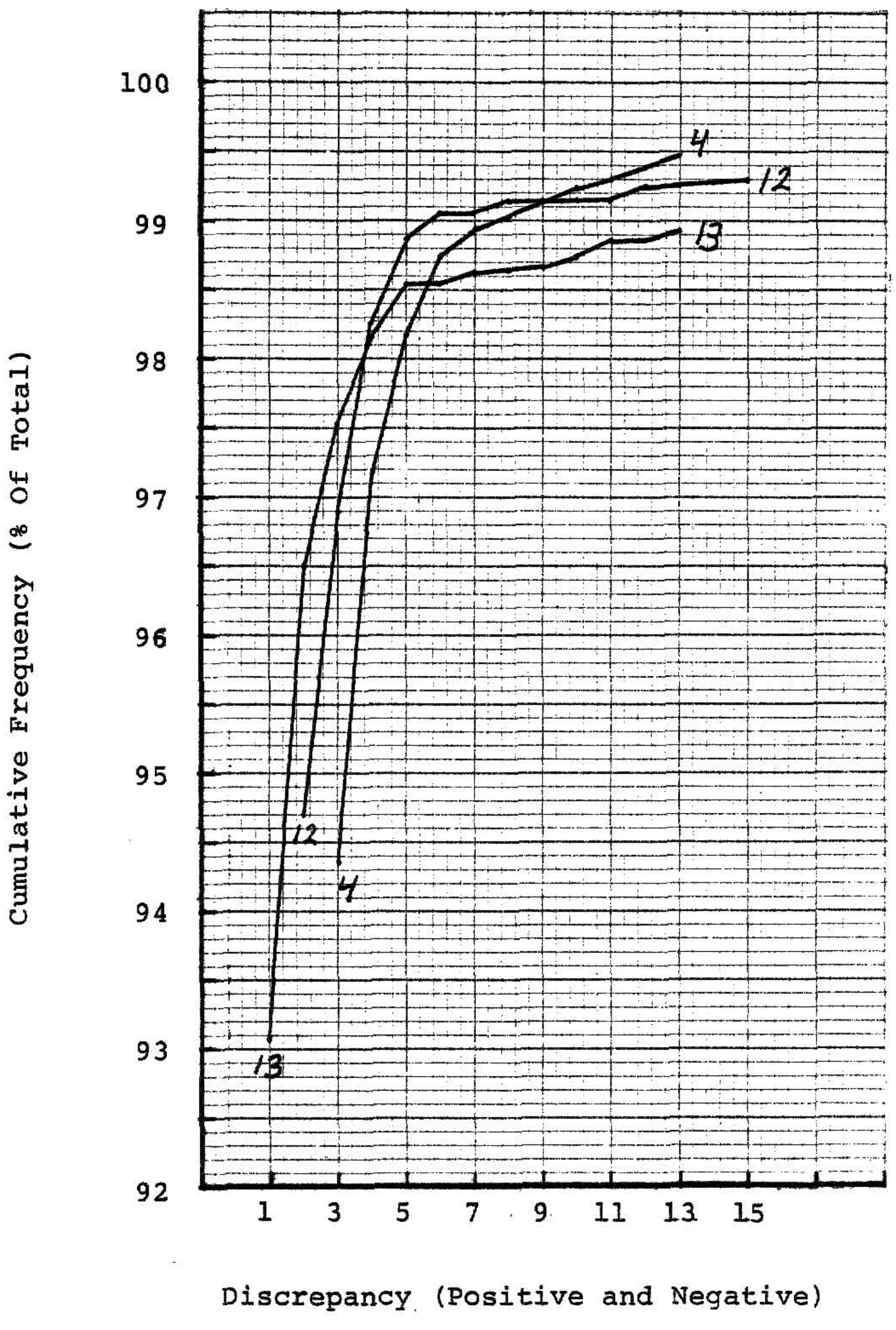


Figure 3.1

Cumulative Frequency vs. Discrepancy As Activity Level Varies of transactions per part increases. Between the 98 and 99.5 percent levels the three graphs exchange places. Here we find that for a given discrepancy size the percent of total parts increases as the number of transactions increase. A possible explanation for this is that there are more errors per part but that some of the errors are offsetting. Thus the more errors the greater the probability of an offsetting error making the end discrepancy smaller.

3.1.2.2 Mean Order Quantity

The order quantities for both the receiving and production phases were analyzed. Experiments 6 and 10 are used to analyze receiving quantities, $\bar{X}_{qr}$, while 18 and 19 are used to analyze production order quantities, $\bar{X}_{qp}$. Contingency tables C-3 and C-4 show chi-square values of 66.52 and 39.86 respectively, each with 18 degrees of freedom. In both cases we can reject the null hypothesis that the distributions are the same at the 1% significance level since $X^2_{.01}(18)=34.8$.

In experiments 18 and 19 $\bar{X}_{qp}$ was varied and the discrepancy distributions were analyzed. In experiments 6 and 10 the process was repeated for $\bar{X}_{qr}$. In each case one of the variables ($\bar{X}_{qp}$ or $\bar{X}_{qr}$) was varied while the other remained constant. When the production order quantity ($\overline{X}_{qp}$) is increased while the receiving order quantity ($\overline{X}_{qr}$) is held constant the ratio of production orders to receiving orders decreases. To simulate a given number of transactions requires more receiving orders. In experiments 18 and 19 the ratios of production quantities to receiving quantities are 3, and 6 respectively. In experiments 6 and 10 the ratios are 6.67 and 3.33 respectively. If the transaction mix is the important factor, experiments 6 and 19 should be compared, as should 10 and 18. The respective chi-square values for these groupings are 38.87 and 38.80 each with 18 degrees of freedom. Again the null hypothesis is rejected at the 1% significance level. It is possible that this is a very sensitive parameter and the slight difference in this ratio affects the system.

3.1.2.3 Standard Deviation Of Order Quantities

Contingency Tables C-5 through C-11 in Appendix C compare experiments with varying standard deviations of order quantity in production and receiving. With the exception of Tables C-5 and C-11 we can accept the null hypothesis that the output distributions are the same.

Table C-5 represents the standard deviation in the receiving phase (σ_{qr}). The computed value for chi-square is 90.42 while $X^2_{.01}(54)$=81.08. Table C-11 represents the standard deviation in the production phase (σ_{qp}).

Here the computed value for chi-square is 38.91 while $\chi^2_{.01}(14)=29.1$. The other experiments were easily accepted at the 10% significance level.

Since 5 out of 7 led to accepting the null hypothesis one could assume that the standard deviation of the order size does not have a significant effect on the inventory system. A larger sample would be helpful to support any conclusions that could be drawn from these experiments.

3.1.2.4 Mean Counting Error

The mean counting error is based on the mean order quantity and the multiplier, as described earlier. The mean counting error is really a pseudo-mean-error because of the altered Poisson as described in section 2.4.2. Tables C-12 through C-16 in Appendix C show the contingency tables for these experiments.

In every case the null hypothesis is rejected and we can say at the 1% significance level that the discrepancy distributions are significantly different. Since many of the discrepancies are caused by counting error, one would expect the mean counting error to affect the discrepancy distribution. Thus the results appear to follow logically from the system design.

Figure 3.2 shows experiments 4, 9, and 10 with mean

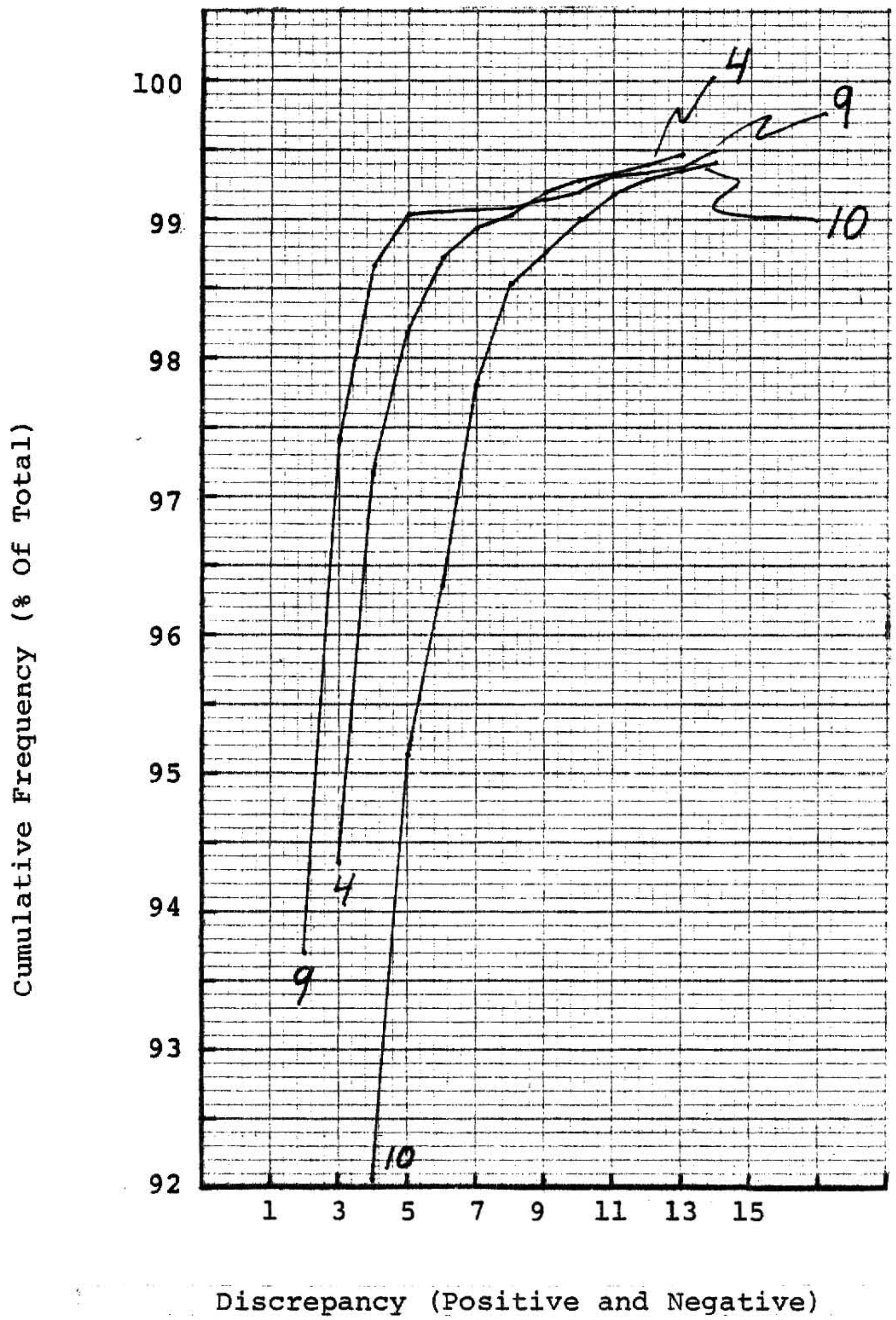


Figure 3.2

Cumulative Frequency vs. Discrepancy As Mean Error Varies errors respectively of 4, 2, and 8. This is representative of the other experiments in this group. Note that as the mean error increases the graphs move to the right. Between 98 and 99.5 percent the graphs begin to switch positions. This was observed earlier when comparing experiments with varying numbers of transactions. The tails are made up of a small proportion of the total number of parts, thus there is less data to compare at these points. It is possible that this could be a random effect and there is not enough data to see the tails stabilize.

3.1.3 Reliabilities

An analysis of the reliability parameters discussed in section 2.4.3 using the chi-square contingency approach follows.

R1 and R2 vary as the reliability for keypunching varies. Experiments 4, 31, and 32 are analyzed in Table C-17. The computed chi-square is 91.39 with 28 degrees of freedom. Since $X^2_{.01}(28)$ equals 48.3 we can reject the null hypothesis at the 1% level. This indicates that the keypunching reliability (R1 and R2) significantly affect the discrepancy distribution.

The transcription reliabilities R3 and R6 are investigated in Table C-18 using experiments 4, 35, and 36. The calculated chi-square is 30.19 with 26 degrees of freedom while $X^2_{.10}(26)=35.6$. The null hypothesis can be accepted even at the 10% significance level. This might be explained because it occurs in the receiving phase and the engineering and production sample phase which have the fewest transactions. R3 and R6 occur only once each. R1 and R2 also occurred in these phases of the system but they occurred a total of 3 times. This may explain the difference between the significance of these two groups of variables.

R4, counting in the production phase, is analyzed by experiments 4, 25, and 26 shown in Table C-19. The calculated chi-square is 123.88 with 28 degrees of freedom while $X^2_{.01}(28)$ equals 48.3. This indicates that R4 is highly significant. The production phase has the highest number of transactions thus a reliability change in this phase would be expected to produce a large change in the inventory system.

Table C-20 investigates experiments 4, 27, and 28 which allow R5 to vary. The calculated chi-square is 84.09 while $X^2_{.01}(26)$ equals 45.6. Thus the null hypothesis can be rejected. This indicates that the reliability of counting and recording, R5, has a significant affect on the discrepancy distribution.

As the inventory size increases there are more valid P/N's which increases the probability that a P/N error will produce a valid P/N. Experiments 4, 29, and 30 in Table C-21 analyze the result of varying R2 and R6 because of a change in inventory size. The calculated chi-square is 53.05 with 28 degrees of freedom while $X^2_{.01}(28)=48.3$. The null hypothesis can be rejected at the 1% level. Thus, the inventory size has a significant effect on the discrepancy distribution.

The remaining reliability, R7, will be investigated using experiments 4, 33, and 34 in Table C-22. The calculated value of chi-square is 192.97 with 26 degrees of freedom while $X^2_{.01}(26)=45.6$. The null hypothesis can be rejected at the 1% significance level. When a bin card is pulled incorrectly the complete quantity is lost to the record. This makes a large error in a case where no offsetting error can occur.

In summary, based on contingency table tests for the experiments in this study, many of the parameters appear to be significant. The question of which parameters are the most significant has not been answered. To answer this question regression analysis will be used.

3.2 Regression Analysis

3.2.1 Purpose

Section 3.1 provided information indicating which parameters are significant. Little useful information is gained, however, because nearly all the parameters seem to be significant. What is needed is the ability to compare all the different parameters or factors simultaneously to determine which are the most significant. The information needed could be supplied with a factorial analysis if there was a simple output parameter to investigate. The correct analysis in this case would be to use cross-classified categorical data models. These models require a great deal of calculation making such analyses impractical without a computer program. Personnel in the statistics laboratory at Kansas State University were not aware of any available programs to handle this analysis. Consequently, they suggested using a stepwise linear regression program in an attempt to determine which variables are the most significant. The following section will discuss the linear regression models to be used.

3.2.2 Regression Models

There are five dependent variables and twenty-two independent variables, including some interactions, to analyze. Table 3.1 lists the variables symbol or expression, its number in the regression model, and its description. There will be five regression models. Each model will have the same set of independent variables but a different dependent variable. As indicated in Table 3.1 each dependent variable is a measure of the discrepancy distribution or the actual discrepancies. Therefore, each regression model will indicate which independent variables explain the greatest variance in its respective measure of the discrepancy distribution.

Some interactions were shown in Table 3.1 while others were omitted. A brief explanation of those included follows. Variables 5 and 22 are reciprocals of one another. They represent the ratio of receiving order quantities to production order quantities and the reciprocal. As these ratios change so does the ratio of receiving transactions to production transactions. This ratio could be important in explaining the discrepancy distribution.

Variables 23 through 26 are used to investigate interactions among the mean counting and keypunch error, hereafter simply mean error, in receiving and various reliabilities associated with error. That is the mean error size interacting with the probability of error in the receiving phase. Variable 27 is the product of mean error in production and the reliability of the counting operation. These interactions are the ones intuitively felt to have some significance.

TABLE 3.1

REGRESSION VARIABLES

Dependent Variables

Symbol	No.	Description
M1	(17)	Mean of discrepancy distribution
M2	(18)	Standard deviation of discrepancy distribution
M3	(19)	Standard 3^{rd} moment of discrepancy distribution
M4	(20)	Standard 4^{th} moment of discrepancy distribution
D	(21)	Discrepancy (physical inventory - recorded inventory)

Independent Variables

Expression	No.	Description
$\bar{X}_{qr}$	(1)	Mean order quantity in receiving
σ_{qr}	(2)	Standard deviation of order quantity (receiving)
$Max_r - Min_r$	(3)	Range of order quantity receiving
$\bar{X}_{er}$	(4)	Mean counting and keypunch error in receiving
$\bar{X}_{qr}/\bar{X}_{qp}$	(5)	Ratio of receiving order quantity to production order quantity
$\bar{X}_{qp}$	(6)	Mean order quantity in production
σ_{qp}	(7)	Standard deviation of order quantity (production)

TABLE 3.1 (Cont.)

Independent Variables (Cont.)

Expression	No.	Description
$(Max_p - Min_p)$	(8)	Range of order quantity production
$\bar{X}_{ep}$	(9)	Mean counting and keypunch error in production
R1	(10)	Keypunch reliability for quantities
R2	(11)	Keypunch reliability for a P/N
R3	(12)	Transcription reliability for a quantity
R4	(13)	Counting reliability
R5	(14)	Reliability of counting and recording a quantity
R6	(15)	Reliability of transcribing a P/N
R7	(16)	Reliability of pulling a bin card
$\bar{X}_{qp}/\bar{X}_{qr}$	(22)	Ratio of production order quantity to receiving order quantity
$(\bar{X}_{er})$ (R1)	(23)	Product of mean counting error (receiving) and keypunch reliability for a quantity
$(\bar{X}_{er})$ (R2)	(24)	Product of mean counting error (receiving) and keypunch reliability for a P/N
$(\bar{X}_{er})$ (R5)	(25)	Product of mean counting error (receiving) and reliability of counting and recording
$(\bar{X}_{er})$ (R6)	(26)	Product of mean counting error (receiving) and reliability of transcribing a P/N
$(\bar{X}_{ep})$ (R4)	(27)	Product of mean counting error production and counting reliability

3.2.3 Regression Results

Tables 3.2 through 3.6 show the last models selected by the stepwise regression for dependent variables 17 through 21 respectively. The standard error of estimate is very low while the multiple correlation coefficient is greater than 0.99 for the regression on variables 17 and 18. The standard error increases while R^2 decreases for the regression on variables 19 through 21 with the model for variable 21 having the poorest fit. The goodness of fit F test shows that all models are highly significant. The models which fit the best are those for the mean and standard deviation of the discrepancy distributions. The ability to predict or explain the higher moments and the actual discrepancies is much less than our ability to predict the first two moments.

The tables also show t values for the variables in the respective models. The tabled $t_{.10}(\infty)$ equals 1.282 while $t_{.01}(\infty)$ equals 2.326. Tables 3.2 through 3.6 show that all variables are significant at the 10% level while only 2 variables are not significant at the 1% level. Many of the variables are extremely significant with t values as large as 1596 on variable 16, Table 3.2. As in the chi-square contingency analysis nearly all the variables are significant. This makes it difficult to obtain useful information from the regression analyses.

Each regression run selected variables 15 and 16 in the top four most significant variables. Variables 15, 16, and 6 are the only variables selected in all five regression models. This list of variables is shortened greatly because of the regression on variable 21 which only selected three variables. The most consistently significant variables are 15 and 16 and 6. Dependent variables 17 and 18 received the best fit from the stepwise regression and each regression selected variable 16 as the most significant followed by variable 15.

Based on the regression analysis R6, R7, and $\bar{X}_{qp}$ corresponding to variable numbers 15, 16, and 6 are the most consistently significant over all dependent variables. These are, however, only a few of the many variables which are highly significant.

TABLE 3.2

REGRESSION RESULTS FOR DEPENDENT VARIABLE 17 (Mean Discrepancy)

Independent Variable	Coefficient	Std. Dev. Coefficient	t Value	Beta Coefficient
1	0.6249 D-03	0.1853 D-04	33.710	0.1947
2	-0.3030 D-03	0.3284 D-04	-9.227	-0.9905 D-02
3	-0.5809 D-04	0.1938 D-04	-2.997	-0.4708 D-02
4	0.1271 D-02	0.8422 D-04	15.100	0.8445 D-02
5	0.2335 D-02	0.1324 D-02	1.764	0.9510 D-02
6	-0.5225 D-02	0.5049 D-04	-103.500	-0.4091
7	0.1330 D-01	0.4181 D-04	318.100	0.1854
8	-0.1644 D-02	0.8125 D-05	-202.300	-0.2770
9	0.2138 D-02	0.1384 D-03	15.450	0.7386 D-02
10	-0.2850 D 02	0.4071	-70.010	-0.1672 D-01
11	-0.1486 D 04	0.3654 D 02	-40.660	-0.1011
12	-0.1227 D 02	0.1781	-68.880	-0.1705 D-01
15	-0.1178 D 05	0.3679 D 02	-320.100	-0.8006
16	0.1753 D 03	0.1099	1596.000	0.3801
22	-0.9662 D-01	0.1157 D-02	-83.480	-0.2352
25	0.6708	0.1942	3.455	0.8194 D-03
27	-0.4203 D 02	0.8648	-48.600	-0.1190 D-01

Standard error of estimate = 0.02426
Multiple correlation coefficient = 0.99727
Goodness of fit, F(17,98982) = 0.1062 D 07
Constant term = -0.0074

$F(17, \infty, 0.99) \approx 1.98$

TABLE 3.3

REGRESSION RESULTS FOR DEPENDENT VARIABLE 18
(STANDARD DEVIATION OF DISCREPANCY DISTRIBUTION)

Independent Variable	Coefficient	Std. Dev. Coefficient	t Value	Beta Coefficient
1	-0.9260 D-03	0.1276 D-03	-7.256	-0.4373 D-01
2	-0.2100 D-01	0.2261 D-03	-92.890	-0.1040
3	0.1183 D-01	0.1335 D-03	88.620	0.1453
4	0.2943	0.1651 D-02	178.200	0.2962
5	-0.3446	0.9113 D-02	-37.810	-0.2126
6	0.1552 D-01	0.3476 D-03	44.660	0.1842
7	-0.1775 D-01	0.2879 D-03	-61.640	-0.3748 D-01
8	0.6902 D-02	0.5594 D-04	123.400	0.1762
9	0.8402 D-01	0.9422 D-03	89.180	0.4397 D-01
10	-0.1190 D 03	0.2803 D 01	-42.460	-0.1058 D-01
12	0.2761 D 03	0.1226 D 01	225.200	0.5815 D-01
13	-0.3933 D 03	0.3140 D 01	-125.300	-0.3135 D-01
14	-0.2632 D 03	0.2342 D 01	-112.400	-0.2796 D-01
15	-0.1273 D 06	0.2533 D 03	-502.700	-1.312
16	-0.5328 D 03	0.7567	-704.100	-0.1750
22	0.1007 D 01	0.7970 D-02	126.400	0.3715
24	-0.1786 D 05	9.1437 D 03	-124.300	-0.3507

Standard error of estimate = 0.16703
Multiple correlation coefficient = 0.99703
Goodness of fit, $F(17, 98982) = 0.9748$ D 06
Constant term = 1.8744

$F(17, \infty, 0.99) \approx 1.98$

TABLE 3.4

REGRESSION RESULTS FOR DEPENDENT VARIABLE 19
(STANDARD THIRD MOMENT OF THE DISCREPANCY DISTRIBUTION)

Independent Variable	Coefficient	St. Dev. Coefficient	t Value	Beta Coefficient
1	0.2156	0.4834 D-02	44.590	2.6220
2	-0.4039	0.8564 D-02	-47.160	-0.5154
3	0.2585	0.5055 D-02	51.140	0.8181
5	-0.1744 D 02	0.3452	-50.520	-2.7730
6	-0.4420	0.1317 D-01	-33.570	-1.3510
7	-0.3101	0.1091 D-01	-28.430	-0.1687
8	0.1174	0.2119 D-02	55.390	0.7720
9	0.4462	0.3569 D-01	12.500	0.6016 D-01
11	0.1650 D 07	0.9531 D 04	173.100	4.381
12	0.2661 D 04	0.4644 D 02	57.290	0.1444
13	-0.5778 D 04	0.1189 D 03	-48.580	-0.1187
14	-0.3164 D 05	0.1593 D 04	-19.870	-0.8660
15	-0.1713 D 07	0.9594 D 04	-178.500	-4.5450
16	0.1737 D 04	0.2866 D 02	60.610	0.1470
22	0.1200 D 02	0.3019	39.740	1.1400
23	0.4050 D 04	0.6062 D 02	66.810	0.1614
25	-0.1390 D 05	0.9087 D 03	-15.290	-0.6628

Standard error of estimate = 6.32687
Multiple correlation coefficient = 0.65920
Goodness of fit, $F(17, 98982) = 4475.0$
Constant term = 10.6585

$F(17, \infty, 0.99) \approx 1.98$

TABLE 3.5

REGRESSION RESULTS FOR DEPENDENT VARIABLE 20
(STANDARD FOURTH MOMENT OF THE DISCREPANCY DISTRIBUTION)

Independent Variable	Coefficient	Std. Dev. Coefficient	t Value	Beta Coefficient
1	0.6112 D 01	0.1448	42.200	2.5480
2	-0.1274 D 02	0.2566	-49.660	-0.5573
3	0.8553 D 01	0.1515	56.470	0.9275
4	0.1611 D 03	0.1874 D 01	85.980	1.432
5	-0.4614 D 03	0.1034 D 02	-44.600	-2.514
6	-0.1208 D 02	0.3945	-30.610	-1.1265
7	-0.6922 D 01	0.3268	-21.180	-0.1291
8	0.2945 D 01	0.6349 D-01	46.380	0.6638
9	0.9572 D 01	0.1082 D 01	8.850	0.4423 D-01
10	-0.1195 D 06	0.3181 D 04	-37.570	-0.9382 D-01
12	0.4037 D 05	0.1392 D 04	29.010	0.7507 D-01
14	-0.1762 D 06	0.2658 D 04	-66.310	-0.1653
15	-0.2896 D 08	0.2875 D 06	-100.700	-2.6340
16	0.9940 D 05	0.8588 D 03	115.700	0.2883
22	0.3216 D 03	0.9045 D 01	35.550	1.0470
24	-0.1738 D 08	0.1630 D 06	-106.600	-3.012
27	0.3593 D 06	0.6758 D 04	53.170	0.1361

Standard error of estimate = 189.57422
Multiple correlation coefficient = 0.63544
Goodness of fit F (17, 98982) = 3943
Constant term = 610.4697

$F(17, \infty, 0.99) \approx 1.98$

TABLE 3.6

REGRESSION RESULTS FOR DEPENDENT VARIABLE 21
(DISCREPANCY)

Independent Variable	Coefficient	Std. Dev. Coefficient	t Value	Beta Coefficient
6	-0.6244 D-03	0.4671 D-03	-1.337	-0.4256 D-02
15	-0.1329 D-05	0.5373 D 03	-24.740	-0.7866 D-01
16	0.1746 D 03	0.1681 D 02	10.380	0.3295 D-01

Standard error of estimate = 3.75864
Multiple correlation coefficient = 0.08638
Goodness of fit, $F(3, 98996) = 248.1$
Constant term = -0.0455

$F(3, \infty, 0.99) \approx 3.78$

3.3 Moments Of The Output Distribution

The output distribution of discrepancies, physical minus recorded inventory, can be described with its moments. Table 3.3 shows the moments of the output distribution for each experiment.

Looking at the mean discrepancies we notice that most of them are negative. The mean and standard deviation of the mean discrepancies are respectively -0.1315 and 0.3324. The means are not far from zero where one might expect them to be. The only explanation for the mean being different from zero is the interaction of the various reliabilities to produce slightly more cumulative negative discrepancies than cumulative positive discrepancies. Since discrepancies are defined to be physical minus recorded inventory this indicates that the recorded inventory is usually larger than the physical inventory. However, the mode of the distributions is zero in every case, as one would expect, indicating that usually no discrepancy occurs.

The mean of the mean discrepancies is relatively constant. That is, the means do not vary a great deal though the parameters in these experiments are varying. This indicates that the input parameters do not greatly affect the mean discrepancy.

The second column of Table 3.7 shows the standard deviation of the discrepancy distribution. The mean and standard deviation of these standard deviations are respectively 3.0703 and 2.2011. From the results of the contingency analysis and the regression run one might expect a larger variation. Again this may indicate that the input parameters do not affect the standard deviation of the discrepancies a great deal in terms of number and size. The percentage variation compared to the mean is large, however.

The third and fourth standard moments show a great deal more variation. In each case the standard deviation is greater than the mean.

This indicates that the first two moments of the error distribution may not be extremely sensitive to the input parameters.

TABLE 3.7

MOMENTS OF THE DISCREPANCY DISTRIBUTION

Experiment	Mean	Standard Deviation	3rd Moment	4th Moment
4	-0.1030	2.7748	13.5296	581.1409
5	-0.1510	2.1871	-5.5601	59.9608
6	-0.1913	2.8177	-4.1838	38.0377
7	-0.2133	2.6882	-4.4533	38.9860
8	-0.2033	2.8554	-3.4764	32.3268
9	-0.1163	2.0201	-7.5606	90.1647
10	-0.1340	2.7027	-3.1918	34.4783
11	-0.1800	2.9132	-3.4840	34.7571
12	-0.1663	1.9876	-7.5860	78.6103
13	-0.2430	2.2995	-8.8205	99.2599
14	-0.1300	2.0205	-6.9859	79.3670
15	-0.0943	2.6181	-4.1629	43.5702
16	-0.1623	2.4740	-3.6599	40.0809
17	-0.1757	3.1218	-3.2460	30.8386
18	-0.2717	3.1146	-2.8519	25.0961
19	-0.1180	2.7870	-3.7255	36.9854
20	-0.1627	2.5984	-3.1689	33.4340
21	-0.1237	3.2428	-2.1356	22.5757
22	-0.2923	3.3934	-2.2561	19.0303
23	-0.2023	2.4035	-5.6333	61.1806

TABLE 3.7 (cont.)

Experiment	Mean	Standard Deviation	3rd Moment	4th Moment
24	-0.1876	3.0430	-2.0369	22.2723
25	-0.1410	2.0297	-5.8894	63.0704
26	-0.2033	2.4118	-6.2958	65.9050
27	-0.1623	2.1931	-7.1346	74.5050
28	-0.1666	2.9702	10.2239	450.6140
29	-0.1363	2.0877	-4.9306	51.3957
30	1.5656	14.9043	8.2932	74.7953
31	-0.1963	2.2834	-8.4595	103.5170
32	-0.1856	2.3564	-5.9844	60.4257
33	0.0470	2.2840	27.9706	1223.8110
34	-0.8526	4.6568	0.0890	90.0325
35	-0.1920	3.1338	7.3886	377.5056
36	-0.0003	3.9459	21.5856	632.0278
Mean.........	-0.1315	3.0703	-1.1452	145.4472
Standard Dev.	0.3324	2.2011	8.5435	249.0564

CHAPTER 4

CONCLUSIONS

4.1 Problems And Limitations

This thesis began from a question posed by an individual with a real problem. In a search of the available literature no solution was found though the general problem was confronted many times. Since little study has been done in the area of predicting inventory errors, many unknown obstacles were encountered along the way. In many cases it is not practical or possible to solve each problem as it arises. In these cases assumptions based on the available knowledge are made and the investigation continues based on these assumptions. As more is learned about a given area of study the assumptions are explained and the total knowledge is increased.

4.1.1 Reliability Data

The literature on human reliability is extremely scarce. The only attempts to compile this type of data were made by American Institute of Research and Sandia

Laboratories. The data that is available is not well documented and in general little verification has been done. There are two reasons why this data is so scarce. The first is concerned with the large number of variables which affect human performance and the second with the difficulty of measuring human performance.

A good example of the second case is given by the Carlson article (1). To obtain estimates of errors in using check proof machines, it was necessary to examine over 2 million checks. The time and expense is such an undertaking make it extremely impractical. The high reliabilities of most human operations make it extremely difficult to obtain accurate reliability estimates.

The reliability estimates used in this study came from whatever source was available. None of the reliabilities applied specifically to an inventory system. Though the estimates are believed reasonable for their respective operations, a great deal of improvement could be made. As the analysis indicated, the reliabilities are important to the output of the inventory simulation. Better estimates of these reliabilities would help to improve this model.

4.1.2 Predicting Error

Predicting human error is another area of study which is relatively undeveloped. This is related to the area of human reliability just discussed. What kind of errors do individuals make? How large are they? These questions and more would apply to transcription errors, counting errors, and keypunch errors. The intuitive ideas which pointed to the Poisson distribution for counting error have not been validated. In short we know very little about predicting human error. The ability to predict it is essential to the modeling of systems in which humans play such a large role.

4.1.3 Verification

Finally, any process attempting to make predictions must be verified. The process of verifying inventory errors would require data not normally collected in the system. In the current study, several years of inventory operation were simulated. It would require several years of study to verify these results. The assumptions regarding simulating one part at a time, reliabilities, error distributions, and the effect of each error on the system all need verification. Do the results apply only to the inventory system modeled or do they apply to other systems? These questions all need further study.

4.2 Application

4.2.1 Important Parameters

The analysis of the data in Chapter 3 indicates that many of the variables in the system are important to the accuracy of the on-hand quantity. The most important variable is the reliability of transcribing a part number in the receiving phase. The second most important variable was the reliability of choosing the correct bin card in the engineering and production sample phase. This amounts to choosing the correct part number. Both of these errors are related to the part number, making it the most important variable. This would indicate that in design of the system the accuracy of the part number is one of the most important factors.

The third most important variable is the mean production quantity. The mean production quantity was found to be significant in the contingency analysis as well. The regression analysis has not given results which differ from the contingency analysis of these variables.

The problem arises that all the variables except the standard deviation of the order quantities, the transcription reliability in the engineering and production sample phase, and possibly the error distribution are significant. This indicates that to accurately model a system accurate data is needed for nearly all the variables investigated.

The application of this information seems to indicate that accuracy is very important in inventory work. This is where the emphasis should be, as opposed to speed. This also indicates that in designing inventory systems any operation which tends to decrease reliability needs to be scrutinized closely.

4.2.2 Detecting Non-Random Error

The goal of this study was to investigate the reliability of the on-hand inventory record. The ability to detect non-random error in an inventory system could be used in auditing and for control purposes. This section will show how this can be done.

When a physical inventory is taken, one expects to see discrepancies. The question of how large these discrepancies should be under random error conditions is what needs to be answered. A control limit so to speak is needed to indicate when the discrepancy is likely to be caused by factors other than random error. One needs to be able to calculate the probability that the discrepancy will be larger than some given amount. To achieve this we will use stochastic inequalities.

Starr and Miller (19) say that Tchebycheff's inequality "... states that for any probability distribution whatsoever there is a simple relationship expressing the probability that the given variable will differ from its mean by some multiple of its standard deviation." In mathematical form it states that the

$$P\ (|y - \mu| \geq k\sigma) \leq 1/k^2 \text{ where } k > 0$$

μ is the population mean and σ is the population standard deviation. The quantities necessary to use this inequality, μ and σ, will be estimated by the sample parameters $\bar{y}$ and s in Table 3.7. Using these estimates of μ and σ approximate control limits can be established.

Suppose one is willing to take a 5% (or 1%) chance of investigating a discrepancy which is actually due to random error, that is, β equals 0.05 (or 0.01). This indicates that $1/k^2$ is equal to 0.05 (or 0.01). Using Tchebycheff's inequality one can calculate how large a discrepancy can be before one should investigate. The discrepancy may be caused by a system error, negligence, pilferage or random error. But only 5% (or 1%) of the discrepancies investigated under this procedure will be due to random factors. Table 4.1 shows control limits calculated for the 5% and 1% levels of β for each experiment.

The numbers in Table 4.1 have been rounded to the next smaller whole number since fractional discrepancies are meaningless in counting objects. This assures that the protection against missing non-random errors is maintained. That is, depending on the rounding required, the true value of β is somewhat greater than 5% or 1%.

Tchebycheff's inequality only requires estimates of the mean and stardard deviation. Since there are many distributions having the same mean and standard deviation the limits are necessarily very wide. If we have more information it is possible to use another inequality which will tighten the limits. Since all the discrepancy distributions have a mode equal to zero, it is logical to use an inequality which uses this information. Such an inequality is presented by Starr and Miller (19: 69-70).

The inequality introduced by Starr and Miller was first shown by Cramér in Mathematical Methods of Statistics. This inequality uses Pearson's measure of skewness, w, where

$$w = \frac{\mu - \text{mode}}{\sigma}$$

The inequality is stated by Starr and Miller as follows:

$$P\ (|y - \mu| \geq k\sigma) \leq \frac{4\ (1 + w^2)}{9\ (k - |w|)^2} \text{ for } k > |w|$$

TABLE 4.1

CONTROL LIMITS FOR DETECTING NON-RANDOM ERROR
(USING TCHEBYCHEFF'S INEQUALITY)

Experiment	β = 5%		β = 1%	
	Positive Discrepancy	Negative Discrepancy	Positive Discrepancy	Negative Discrepancy
4	12	12	27	27
5	9	9	21	22
6	12	12	27	28
7	11	12	26	27
8	12	12	28	28
9	8	9	20	20
10	11	12	26	27
11	12	13	28	29
12	8	9	19	20
13	10	10	22	23
14	8	9	20	20
15	11	11	26	26
16	10	11	24	24
17	13	14	31	31
18	13	14	30	31
19	12	12	27	27
20	11	11	25	26
21	14	14	32	32
22	14	15	33	34
23	10	10	23	24

TABLE 4.1 (Cont.)

Experiment	β = 5%		β = 1%	
	Positive Discrepancy	Negative Discrepancy	Positive Discrepancy	Negative Discrepancy
24	13	13	30	30
25	8	9	20	20
26	10	10	23	24
27	9	9	21	22
28	13	13	29	29
29	9	9	20	21
30	68	65	150	147
31	10	10	22	23
32	10	10	23	23
33	10	10	22	22
34	19	21	45	47
35	13	14	31	31
36	17	17	39	39
Mean	13.36	13.03	30.42	30.00
Std. Dev.	9.63	10.00	21.71	22.28
*Mean	11.75	11.31	26.78	26.25
*Std. Dev.	2.68	2.51	5.87	5.79

*Mean and standard deviation excluding experiment 30

TABLE 4.2

CONTROL LIMITS FOR DETECTING NON-RANDOM ERROR
(USING PEARSON'S MEASURE OF SKEWNESS)

Experiment	β = 5%		β = 1%	
	Positive Discrepancy	Negative Discrepancy	Positive Discrepancy	Negative Discrepancy
4	8	8	18	18
5	6	6	14	14
6	8	8	18	19
7	8	8	18	18
8	8	8	19	19
9	6	6	13	13
10	8	8	18	18
11	8	9	19	19
12	5	6	13	13
13	6	7	15	15
14	6	6	13	13
15	7	7	17	17
16	7	7	16	16
17	9	9	20	21
18	9	9	20	21
19	8	8	18	18
20	7	8	17	17
21	9	9	21	21
22	10	10	22	23
23	7	7	16	16

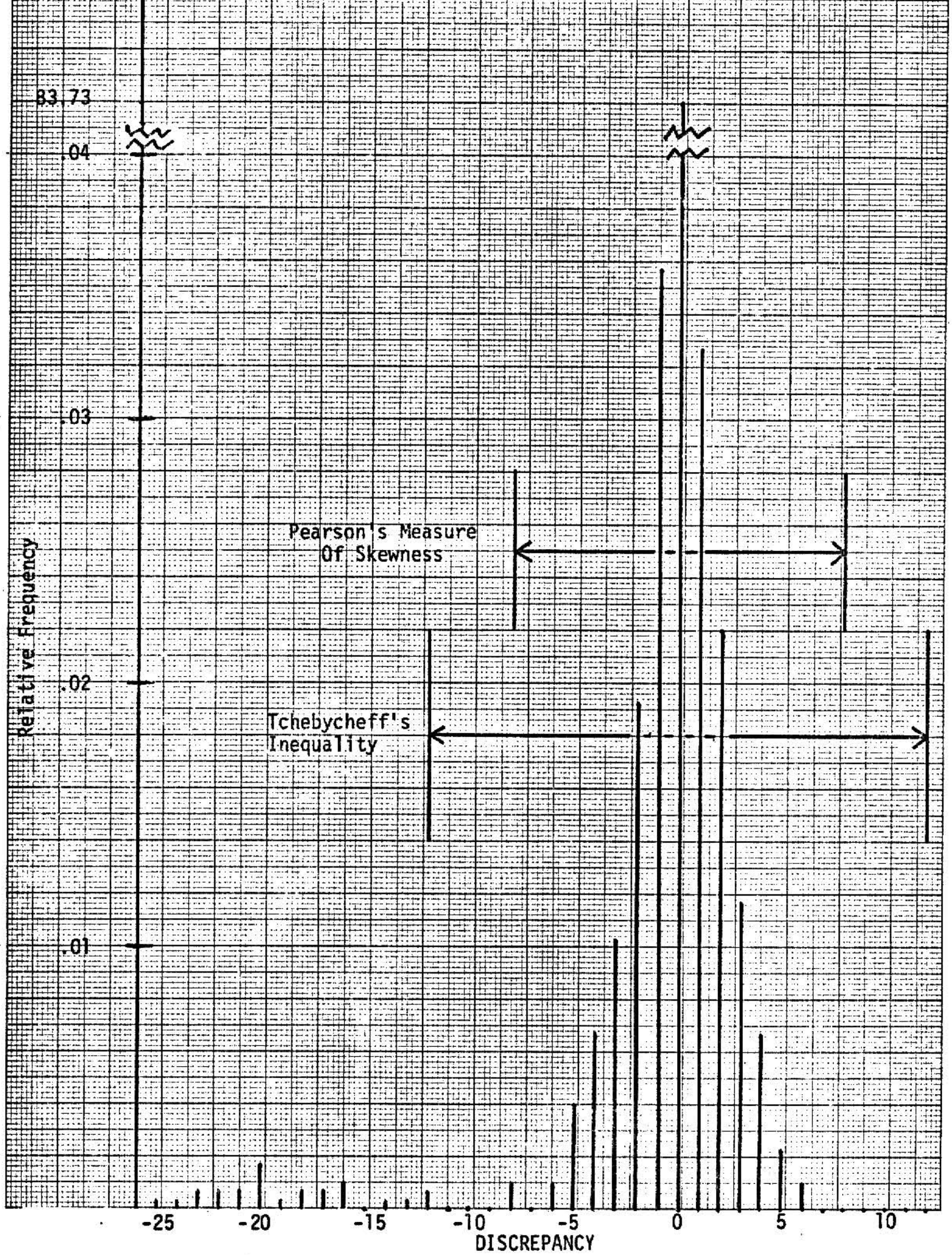
TABLE 4.2 (Cont.)

Experiment	β = 5%		β = 1%	
	Positive Discrepancy	Negative Discrepancy	Positive Discrepancy	Negative Discrepancy
24	9	9	20	20
25	6	6	13	13
26	7	7	16	16
27	6	6	14	14
28	8	9	19	20
29	6	6	13	14
30	47	44	103	99
31	6	7	15	15
32	7	7	15	16
33	6	6	15	15
34	14	15	31	33
35	9	9	20	21
36	11	11	26	26
Mean	8.85	8.97	20.15	20.33
Std. Dev.	7.08	6.55	15.37	14.72
*Mean	7.66	7.88	17.56	17.88
*Std. Dev.	1.81	1.86	3.93	4.23

*Mean and standard deviation excluding experiment 30.

FIGURE 4.1

Control Limit Example For Experiment 4



where the distribution is assumed to be unimodal. As with the Tchebycheff inequality, we must estimate the population parameters with our sample parameters.

Table 4.2 shows control limits calculated with this inequality which makes use of the mode. Note that for a given value of β and a given experiment Tchebycheff's inequality always produces a larger control limit. Because of this larger control limit the probability of investigating a true random error situation is less than the stated value. This also indicates that the ability to detect random error is sacrificed since β is overestimated. For this reason the inequality using Pearson's estimate of skewness is preferred and will be used in the remaining discussion.

If the simulation and parameters of experiment 4 accurately represent an inventory item, control limits should be established as follows. Table 4.2 shows control limits calculated for β equal to 0.05 or 0.01. Due to the cost of investigating the inventory system suppose one can only accept a 5% chance of making an investigation when it is not required. If the absolute value of the discrepancy is 8 or greater, one would assume that it was caused by something other than random error. There is a 5% chance that the discrepancy would be ≥ 8 and be caused by random error. The decision rule would be to investigate the inventory system and the use of the part closely if the absolute value of the discrepancy were greater than or equal to 8. If one can only accept a 1% chance of making an incorrect decision, the rule is to investigate those parts with an absolute value of discrepancy $\geq$ 18. A similar approach could be used for the remaining experiments.

Looking at the values calculated for the other experiments it is apparent that the numbers for the control limits do not vary a great deal except for experiment 30. The mean and standard deviation of these control limits are shown in Table 4.2. The means and standard deviations for the 5% level are respectively 8, 8, 8, and 7. If experiment 30 is eliminated, they are 7, 7, 2, and 2 respectively. With the exception of experiment 30 the decision rules do not vary a great deal over all the experiments. Experiment 30 represents a large inventory size, which increases the probability of picking a valid P/N by chance. This is an important parameter as the analysis previously indicated.

Based upon this, if the inventory size remains constant or nearly so, the decision rules for β =0.05 have a mean of 7 and a standard deviation of 2 if the model and parameters of the simulation are valid.

In conclusion, more study needs to be done to verify the results of this investigation. Based upon the results of verification it may be necessary to obtain better estimates of reliabilities involved, transcription errors, counting errors, and keypunch errors. The analysis of the model could possibly have been improved through the use of cross-classified categorical data models which were not used because a program was not available.

If the results of this simulation model were verified and found to be valid, the decision rules shown here could be applied to an inventory system to achieve better control. The reliability of the inventory system and its security could be determined through the use of this model. In addition it could provide selection criteria for judging alternate inventory systems.

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APPENDIX A

DERIVATION OF ALTERED POISSON

Definition of the Poisson probability mass function:

$$p(x,\lambda) = \frac{\lambda^{x} e^{-\lambda}}{x\,!} \qquad x = 0,\ 1,\ 2,\ \ldots$$

Remembering that $\sum_{x=0}^{\infty} p(x,\lambda)$ must equal unity in order to have a proper probability mass function, we can not simply remove the probability of a zero occurrance.

Since $1-p(0,\lambda) = \sum_{x=1}^{\infty} p(x,\lambda)$ and $p(0,\lambda) = e^{-\lambda}$ we can construct a proper probability mass function as follows:

$$p'(x,\lambda) = K\frac{\lambda^{x}}{x!} \qquad \text{where } x = 1,\ 2,\ 3,\ \ldots$$

$$\text{and} \quad K = \frac{e^{-\lambda}}{(1-e^{-\lambda})} .$$

APPENDIX B

PROGRAM LISTING

```
      SUBROUTINE CERR(IQTY,FRACTN)
      REAL LMDA
      LMDA=FRACTN*FLOAT(IQTY)
      RNDM=UNI(0)
      P=(EXP(-LMDA))/(1.-EXP(-LMDA))
      IX=1
      CUMP=0.0
   50 P=P*LMDA/FLOAT(IX)
      IF(P.LE.1.00E-08)GO TO 10
      CUMP=CUMP+P
      IF(RNDM.LE.CUMP)GO TO 10
      IX=IX+1
      GO TO 50
   10 RNDM=UNI(0)
      ISIGN=1
      IF(RNDM.GE.0.5)ISIGN=-1
      IQTY=IQTY+(IX*ISIGN)
      RETURN
      END
```

```
      INTEGER FUNCTION UDIST(UPPER,LOWER)
      REAL LOWER
C     NORMAL DISTRIBUTION FOR ORDER QUANTITIES
      IF(UPPER.EQ.LOWER)GO TO 1
      RANGE=UPPER-LOWER
      XBAR=RANGE/2.0
      SIGMA=RANGE/6.0
      RDIST=(RNOR(0)*SIGMA)+XBAR
      IF(IFIX(RDIST).GE.UPPER)GO TO 1
      IF(IFIX(RDIST).LE.LOWER)GO TO 2
      X2=AINT(RDIST)
      X=AMOD(RDIST,X2)
      I=0
      IF(X.GT.0.5)I=1
      UDIST=INT(RDIST)+I
      GO TO 10
    2 UDIST=IFIX(LOWER)
      GO TO 10
    1 UDIST=IFIX(UPPER)
   10 CONTINUE
      RETURN
      END
```

```
      LOGICAL LN(5),ECHO,OUTLAR
      REAL RLREC(5),RLPRD(2),RSMP(4),RAN(5),LOWER1,LOWER2,LOWER3
      REAL AMCMT(4)
      INTEGER CODR,TACT,SPSIZE,COUNT,ORDER,PAPER,PHY,TRNSCT,UDIST
      DIMENSION IDIF(101)
      DO 1001 I=1,101
 1001 IDIF(I)=0
      DO 1002 I=1,4
 1002 AMOMT(I)=0.0
      MCMT=0
C
C
C     NPART= NO.OF PARTS TO SIMULATE
C     TACT=TOTAL ACTIVITY IN TRANSACTIONS
C
C
C     RECEIVING: FCTN1=FRACTION OF QUANTITY TO GET LMDA FOR TRANSCRIPTION ERRORS
C                (RECEIVING), FCTN2= FRACTION OF QUANTITY TO GET LMDA FOR
C                KEYPUNCH ERRORS(RECEIVING)
C                UPPER1 & LOWER1 = MAX & MIN ORDER QUANTITIES FOR RECEIVING
C                RLREC= RELIABILITY TREE RECEIVING
C
C
C     PRODUCTION PULL: FCTN3= FRACTION OF QUANTITY TO GET LMDA FOR TRANSCRIPTION
C                      ERRORS,UPPER2 & LOWER2 = MAX &MIN LOTSIZE
C                      RLPRD= RELIABILITY OF SAMPLE TREE
C
C
C     SAMPLE: FCTN4 = FRACTION OF QUANTITY TO GET LMDA FOR TRANSCRIPTION ERROR
C             FCTN5= FRACTION OF QUANTITY TO GET LMDA FOR KEYPUNCH ERRORS
C             UPPER3 & LOWER3 = THE MAX & MIN SAMPLE SIZE
C             RSMP= RELIABILITY OF SAMPLE TREE
C             NSAMP=NO. OF TRANSACTIONS IN THE SAMPLE PHASE
C
C
C     STARTING RANDOM NUMBER SEEDS
C
      READ(5,206)ISED1,ISED2
  206 FORMAT(2I12)
      READ(5,202)TACT,NPART,NSAMP
  202 FORMAT(8I10)
      READ(5,204)FCTN1,FCTN2,UPPER1,LOWER1
      READ(5,204)(RLREC(I),I=1,5)
      READ(5,204)FCTN3,UPPER2,LOWER2
      READ(5,204)(RLPRD(I),I=1,2)
      READ(5,204)FCTN4,FCTN5,UPPER3,LOWER3
      READ(5,204)(RSMP(I),I=1,4)
  204 FORMAT(5F10.4)
      OUTLAR=.FALSE.
      ECHO=.TRUE.
```

```
      ISED3=0
      ISED4=0
      GO TO 700
   30 ECHO=.FALSE.
C
C     SET RANDOM NO. GENERATOR WITH STARTING SEEDS
C
      CALL RSTART(ISED1,ISED2)
C
C     LOOP FOR NO. OF PARTS
C
      NPART=NPART/15
      DO 850 M=1,15
      DO 1 JJ=1,NPART
      PAPER=0
      PHY=0
      TRNSCT=0
      NSMPCK=0
   28 CONTINUE
C
C     INITIALIZATION OF TREE PATH FOR RECEIVING
C     GET 5 RANDOM NUMBERS
C
      DO 10 I=1,5
      RAN(I)=UNI(0)
C
C     INITIALIZE LOGICAL VECTOR LN TO TRUE
C
      LN(I)=.TRUE.
C
C     SET LOGIC FOR TREE ANALYSIS
C     LN(I)= CONDITION AT TREE LEVEL (1 BEING TOP)
C
      IF(RAN(I).GT.RLREC(I))LN(I)=.FALSE.
   10 CONTINUE
      CODR=UDIST(UPPER1,LOWER1)
      COUNT=CODR
      ORDER=CODR
C
C     TREE OPERATIONS FOR RECEIVING
C     FIRST CHECK FOR SUCCESS
C
      IF(LN(1).AND.LN(2).AND.LN(3).AND.LN(4).AND.LN(5))GO TO 24
      IF(LN(1).AND.LN(2))GO TO 16
      IF(.NOT.LN(5))GO TO 26
      PHY=PHY+COUNT
      GO TO 26
   16 IF(LN(3))GO TO 22
      CALL CERR(ORDER,FCTN1)
      IF(LN(4))GO TO 20
```

```
   18 CALL CERR(ORDER,FCTN2)
   20 PAPER=PAPER+ORDER
      IF(.NCT.LN(5))GO TO 26
      PHY=PHY+COUNT
      GO TO 26
   22 IF(.NCT.LN(4))GO TO 18
      PAPER=PAPER+ORDER
      GO TO 26
   24 PAPER=PAPER+ORDER
      PHY=PHY+CCUNT
   26 TRNSCT=TRNSCT+1
      IF(TRNSCT.GE.TACT)GO TC 999
C
C     RECEIVING PHASE COMPLETE
C
C
C     PRODUCTICN PULL PHASE
C
   55 CCNTINUE
C
C     INITIALIZE TREE PATH FOR PRODUCTION PULLS
C     GET 2 RANDOM NUMBERS
C
      DO 50 I=1,2
      RAN(I)=UNI(0)
C
C     INITIALIZE LOGICAL VECTOR
C
      LN(I)=.TRUE.
C
C     SET LCGIC FOR TREE ANALYSIS
C
      IF(RAN(I).GT.RLPRD(I))LN(I)=.FALSE.
   50 CONTINUE
      NLOT=UDIST(UPPER2,LOWER2)
      CCUNT=NLCT
      PAPER=PAPER-NLOT
C
C     PRODUCTICN PULL DECISICN TREE
C
      IF(LN(1).AND.LN(2))GC TC 52
      IF(.NCT.LN(1))GO TO 54
      CALL CERR(CCUNT,FCTN3)
   52 PHY=PHY-COUNT
   54 TRNSCT=TRNSCT+1
      IF(TRNSCT.GE.TACT)GO TC 999
      LIMIT=2*IFIX(UPPER2)
      IF((PHY.LE.LIMIT).OR.(PAPER.LE.LIMIT))GO TO 28
      IF(NSMPCK.GE.NSAMP)GO TO 55
C
```

```
C      PRODUCTION PULL PHASE COMPLETE
C
C
C      PRODUCTION AND ENGINEERING SAMPLES
C      INITIALIZE TREE PATH
C
       DO100 I=1,4
C
C      GET 4 RANDOM NUMBERS
C
       RAN(I)=UNI(0)
C
C      INITIALIZE LOGICAL VECTOR TO TRUE
C
       LN(I)=.TRUE.
C
C      SET TREE PATH
C
       IF(RAN(I).GT.RSMP(I))LN(I)=.FALSE.
  100  CONTINUE
       TRNSCT=TRNSCT+1
       NSMPCK=NSMPCK+1
C
C      PRODUCTION SAMPLE DECISION TREE
C
       SPSIZE=UDIST(UPPER3,LOWER3)
       COUNT=SPSIZE
       ORDER=SPSIZE
       IF(LN(1).AND.LN(2).AND.LN(3).AND.LN(4))GO TO 108
       IF(LN(1))GO TO 102
       IF(.NOT.LN(2))GO TO 110
       PHY=PHY-COUNT
       GO TO 110
  102  IF(LN(2))GO TO 104
       COUNT=0
  104  IF(LN(3))GO TO 106
       CALL CERR(ORDER,FCTN4)
  106  IF(LN(4))GO TO 108
       CALL CERR(ORDER,FCTN5)
  108  PAPER=PAPER-ORDER
       PHY=PHY-COUNT
  110  CONTINUE
       GO TO 55
  999  CONTINUE
C
C      END OF PRODUCTION PULL PHASE
C
C
C      BEGINNING OF DATA COLLECTION
C
```

```
      IDIFF=PHY-PAPER
      MOMT=MOMT+IDIFF
      IF(IABS(IDIFF).GT.50)GO TO 1010
      ID=IDIFF+51
      IDIF(ID)=IDIF(ID)+1
      GO TO 1
 1010 IF(OUTLAR)GO TO 1000
      OUTLAR=.TRUE.
      WRITE(6,651)
  651 FORMAT('1',14X,'VALUES EXCEEDING HISTOGRAM BOUNDARIES')
 1000 WRITE(6,650)IDIFF
  650 FORMAT(' ',14X,I11)
    1 CONTINUE
C
C     DATA ANALYSIS
C
      DENOM=FLOAT(M*JJ)
      AMOMT(1)=FLOAT(MOMT)/DENOM
      DO 70 I=1,101
      II=I-51
      DO 70 K=2,4
   70 AMOMT(K)=AMOMT(K)+(((FLOAT(II)-AMOMT(1))**K)*FLOAT(IDIF(I)))
      AMOMT(2)=SQRT(AMOMT(2)/DENOM)
      AMOMT(3)=(AMOMT(3)/DENOM)/(AMOMT(2)**3)
      AMOMT(4)=(AMOMT(4)/DENOM)/(AMOMT(2)**4)
      WRITE(6,615)
      WRITE(6,616)(AMOMT(K),K=1,4)
      DO 800 KKK=1,4
  800 AMOMT(KKK)=0.0
  850 CONTINUE
      NPART=NPART*15
C
C     BEGINNING OF REPORTING PHASE
C
      CALL RSTOP(ISED3,ISED4)
  700 WRITE(6,600)
  600 FORMAT('1',//,32X,'A SIMULATION OF INVENTORY ERRORS')
      WRITE(6,601)NPART
  601 FORMAT('0',///,15X,'NUMBER OF PARTS IN THIS SIMULATION    = ',I6)
      WRITE(6,602)TACT
  602 FORMAT(' ',14X,'TOTAL NUMBER OF TRANSACTIONS / PART  = ',I6)
      WRITE(6,603)
  603 FORMAT('0',/,15X,'RECEIVING PHASE:')
      WRITE(6,604)UPPER1
  604 FORMAT('0',20X,'MAXIMUM ORDER QUANTITY ....... = ',F6.0)
    . WRITE(6,605)LOWER1
  605 FORMAT(' ',20X,'MINIMUM ORDER QUANTITY ....... = ',F6.0)
      WRITE(6,606)FCTN1
  606 FORMAT('0',20X,'LAMBDA FOR TRANSCRIPTION ERROR = ',F6.4,'  X  QUAN
     1TITY')
```

```
      WRITE(6,607)FCTN2
  607 FORMAT(' ',20X,'LAMBDA FOR KEYPUNCH ERROR .... = ',F6.4,'  X  QUAN
     1TITY')
      WRITE(6,609)
  609 FORMAT('0',20X,'RELIABILITIES:')
      WRITE(6,608)(RLREC(I),I=1,5)
  608 FORMAT('0',16X,5F13.7)
      WRITE(6,610)
  610 FORMAT('0',14X,'PRODUCTION PULL PHASE:')
      WRITE(6,604)UPPER2
      WRITE(6,605)LOWER2
      WRITE(6,606)FCTN3
      WRITE(6,609)
      WRITE(6,608)(RLPRD(I),I=1,2)
      WRITE(6,611)NSAMP
  611 FORMAT('0',14X,'PRODUCTION AND ENGINEERING SAMPLES:  = ',I5)
      WRITE(6,604)UPPER3
      WRITE(6,605)LOWER3
      WRITE(6,606)FCTN4
      WRITE(6,607)FCTN5
      WRITE(6,609)
      WRITE(6,608)(RSMP(I),I=1,4)
      WRITE(6,612)ISED1,ISED3,ISED2,ISED4
  612 FORMAT('0',14X,'RANDOM GENERATOR SEEDS:',//,21X,'START:      ',I12,1
     10X,'END:      ',I12,/31X,I12,18X,I12)
      IF(ECHC)GO TO 30
      WRITE(6,615)
  615 FORMAT('0',14X,'MOMENTS OF FOLLOWING DISTRIBUTION:',//,23X,'MEAN',
     16X,'STD.DEV.',5X,'STD. 3RD',5X,'STD. 4TH',/)
      WRITE(6,616)(AMCMT(K),K=1,4)
  616 FORMAT(' ',20X,4(F8.4,5X))
      WRITE(6,600)
      WRITE(6,614)
  614 FORMAT('0',/,15X,'DIFFERENCE  FREQUENCY  PERCENT    DIFFERENCE  F
     1REQUENCY  PERCENT',/,15X,'PHY-RECORD',13X,'OF TOTAL    PHY-RECORD',
     214X,'OF TOTAL',/)
      PER=FLOAT(NPART)
      DO 1003 I=1,50
      K=102-I
      II=I-51
      KK=-II
      PER1=(FLOAT(IDIF(I))/PER)*100.
      PER2=(FLOAT(IDIF(K))/PER)*100.
 1003 WRITE(6,613)II,IDIF(I),PER1,KK,IDIF(K),PER2
      II=0
      PER1=(FLOAT(IDIF(51))/PER)*100.
      WRITE(6,613)II,IDIF(51),PER1
  613 FORMAT(' ',18X,I3,8X,I4,6X,F5.2,9X,I2,9X,I4,6X,F5.2)
      STOP
      END
```

A SIMULATICN OF INVENTCRY ERRORS

```
NUMBER OF PARTS IN THIS SIMULATICN       =    2000
TOTAL NUMBER OF TRANSACTIONS / PART      =     200

RECEIVING PHASE:

         MAXIMUM ORDER QUANTITY ....... =    300.
         MINIMUM ORDER QUANTITY ....... =    100.

         LAMBDA FOR TRANSCRIPTICN ERROR = 0.0200  X  QUANTITY
         LAMBDA FOR KEYPUNCH ERROR .... = 0.0200  X  QUANTITY

         RELIABILITIES:

         0.9999999    0.9999999    0.9987000    0.9989000    1.000000

PRODUCTICN PULL PHASE:

         MAXIMUM ORDER QUANTITY ....... =    110.
         MINIMUM ORDER QUANTITY ....... =     10.

         LAMBDA FOR TRANSCRIPTICN ERROR = 0.0200  X  QUANTITY
         RELIABILITIES:

         1.0000000    0.9990000

PRODUCTICN AND ENGINEERING SAMPLES:  =     10

         MAXIMUM ORDER QUANTITY ....... =     40.
         MINIMUM ORDER QUANTITY ....... =      5.

         LAMBDA FOR TRANSCRIPTICN ERROR = 0.0500  X  QUANTITY
         LAMBDA FOR KEYPUNCH ERROR .... = 0.0500  X  QUANTITY
         RELIABILITIES:

         0.9990000    1.0000000    0.9974000    0.9989000

RANDOM GENERATOR SEEDS:

         START:      -283961757          END:       -401530045
                     -142767859                      -18603790

MOMENTS OF FCLLOWING DISTRIBUTION:

            MEAN        STD.DEV.      STD. 3RD      STD. 4TH

          -0.1675        2.2155       -4.9464       48.6376
```

A SIMULATION OF INVENTORY ERRORS

DIFFERENCE PHY-RECORD	FREQUENCY	PERCENT OF TOTAL	DIFFERENCE PHY-RECORD	FREQUENCY	PERCENT OF TOTAL
-50	0	0.0	50	0	0.0
-49	0	0.0	49	0	0.0
-48	0	0.0	48	0	0.0
-47	0	0.0	47	0	0.0
-46	0	0.0	46	0	0.0
-45	0	0.0	45	0	0.0
-44	0	0.0	44	0	0.0
-43	0	0.0	43	0	0.0
-42	0	0.0	42	0	0.0
-41	0	0.0	41	0	0.0
-40	0	0.0	40	0	0.0
-39	0	0.0	39	0	0.0
-38	0	0.0	38	0	0.0
-37	0	0.0	37	0	0.0
-36	0	0.0	36	0	0.0
-35	0	0.0	35	0	0.0
-34	0	0.0	34	0	0.0
-33	0	0.0	33	0	0.0
-32	0	0.0	32	0	0.0
-31	0	0.0	31	0	0.0
-30	0	0.0	30	0	0.0
-29	0	0.0	29	0	0.0
-28	0	0.0	28	0	0.0
-27	0	0.0	27	0	0.0
-26	0	0.0	26	0	0.0
-25	2	0.10	25	0	0.0
-24	2	0.10	24	0	0.0
-23	0	0.0	23	0	0.0
-22	1	0.05	22	0	0.0
-21	0	0.0	21	0	0.0
-20	1	0.05	20	0	0.0
-19	0	0.0	19	0	0.0
-18	1	0.05	18	0	0.0
-17	1	0.05	17	0	0.0
-16	0	0.0	16	0	0.0
-15	3	0.15	15	0	0.0
-14	0	0.0	14	0	0.0
-13	2	0.10	13	0	0.0
-12	2	0.10	12	0	0.0
-11	2	0.10	11	0	0.0
-10	1	0.05	10	0	0.0
-9	3	0.15	9	0	0.0
-8	3	0.15	8	0	0.0
-7	2	0.10	7	3	0.15
-6	3	0.15	6	10	0.50
-5	12	0.60	5	10	0.50
-4	34	1.70	4	25	1.25
-3	44	2.20	3	50	2.50
-2	85	4.25	2	75	3.75
-1	93	4.65	1	110	5.50
0	1420	71.00			

APPENDIX C

CONTINGENCY TABLES

TABLE C-1

COUNTING ERROR DISTRIBUTION

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
1	10	5	7	7	16	19	35	35	57	102
2	14	7	9	6	10	10	7	31	57	98
3	15	9	5	8	9	17	17	37	51	95

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
1	1481	78	53	35	23	18	5	9	5
2	1549	76	43	25	18	13	10	10	7
3	1476	101	54	30	20	17	7	13	19

Chi-Square = 55.76, d.f. = 36

TABLE C-2

ACTIVITY LEVEL

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-6	-5	-4	-3	-2	-1
4	7	15	16	15	43	69	129	139
12	13	12	6	12	20	31	58	107
13	13	24	5	7	10	16	51	65

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	≥5
4	2148	166	109	72	41	31
12	2512	98	66	35	20	10
13	2659	68	52	15	10	5

Chi-Square = 366.27, d.f. = 26

TABLE C-3

MEAN ORDER QUANTITY (RECEIVING)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	-8	-7	-6	-5	-4	-3	-2	-1
6	16	31	10	14	12	16	25	21	70	138
10	8	21	13	24	26	38	43	46	79	126

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
6	2301	141	67	41	29	16	15	19	18
10	2175	123	66	56	47	40	25	33	11

Chi-Square = 66.52, d.f. = 18

TABLE C-4

MEAN ORDER QUANTITY (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
18	15	35	32	21	31	35	50	47	74	78
19	14	26	16	8	12	21	31	53	74	108

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
18	2226	88	58	53	43	32	27	32	23
19	2274	103	75	47	39	29	24	29	17

Chi-Square = 39.86, d.f. = 18

TABLE C-5

STANDARD DEVIATION OF ORDER QUANTITY (RECEIVING)

EXPERIMENT NO.	≤-20	≤-10	-8	-7	-6	-5	-4	-3	-2	-1
				DISCREPANCY						
6	16	31	10	14	12	16	25	21	70	138
7	15	23	13	11	17	20	31	34	83	127
8	15	36	21	10	18	9	20	28	85	131
11	15	40	12	10	8	7	12	29	86	155

EXPERIMENT NO.	0	1	2	3	4	5	6	≥7	≥9
				DISCREPANCY					
6	2301	141	67	41	29	16	15	19	18
7	2292	117	72	49	29	23	19	15	10
8	2283	149	63	38	13	16	12	23	30
11	2279	152	71	41	11	10	7	25	30

Chi-Square = 90.42, d.f. = 54

TABLE C-6

STANDARD DEVIATION OF ORDER QUANTITY (RECEIVING)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
4	7	15	8	2	6	15	43	69	129	139
5	8	16	8	6	5	18	35	57	100	140

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7
4	2148	166	109	72	41	15	10	6
5	2233	160	88	57	30	18	13	8

Chi-Square = 16.5, d.f. = 17

TABLE C-7

STANDARD DEVIATION ORDER QUANTITY (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
21	11	34	30	27	38	44	44	64	51	54
22	16	41	42	29	47	48	60	51	43	44

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
21	2196	74	60	54	58	43	35	45	38
22	2219	50	50	50	45	45	45	48	27

Chi-Square = 21.13,d.f. =18

TABLE C-8

STANDARD DEVIATION OF ORDER QUANTITY (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
19	14	26	16	8	12	21	31	53	74	108
20	7	26	14	13	18	26	47	59	81	89

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
19	2274	103	75	47	39	29	24	29	17
20	2275	88	88	51	41	22	17	24	14

Chi-Square = 16.49, d.f. = 18

TABLE C-9

STANDARD DEVIATION OF ORDER QUANTITY (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
17	16	28	29	20	23	20	35	65	72	90
18	15	35	32	21	31	35	50	47	74	78

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
17	2200	117	75	51	40	33	25	36	25
18	2226	88	58	53	43	32	27	32	23

Chi-Square = 19.67, d.f. = 18

TABLE C-10

STANDARD DEVIATION OF ORDER QUANTITY (PRODUCTION)

EXPERIMENT	DISCREPANCY									
NO.	≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
15	13	23	14	9	10	14	11	26	80	142
16	7	26	10	14	17	22	21	35	85	142

EXPERIMENT	DISCREPANCY								
NO.	0	1	2	3	4	5	6	≥7	≥9
15	2282	148	72	32	24	21	23	25	17
16	2278	151	63	48	20	12	14	21	14

Chi-Square = 22.07, d.f. = 18

TABLE C-11

STANDARD DEVIATION OF ORDER QUANTITY (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-6	-5	-4	-3	-2	-1
4	7	15	16	15	43	69	129	139
14	12	7	6	17	25	49	95	181

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
14	2248	161	94	60	26	11	8

Chi-Square = 38.91, d.f. = 14

TABLE C-12

MEAN ERROR (RECEIVING)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-5	-4	-3	-2	-1
4	7	15	31	43	69	129	139
9	7	18	7	14	48	124	183
10	8	21	101	43	46	79	126

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	≥5
4	2148	166	109	72	41	31
9	2171	216	118	63	23	8
10	2175	123	66	56	47	109

Chi-Square = 318.32, d.f. = 24

TABLE C-13

MEAN ERROR (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
18	15	35	32	21	31	35	50	47	74	78
22	16	41	42	29	47	48	60	51	43	44

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
18	2226	88	58	53	43	32	27	32	23
22	2219	50	50	50	45	45	45	48	27

Chi-Square = 48.63, d.f. = 18

TABLE C-14

MEAN ERROR (PRODUCTION)

EXPERIMENT	DISCREPANCY									
NO.	≤-20	≤-10	≤-8	-7	-6	-5	-4	-3	-2	-1
17	16	28	29	20	23	20	35	65	72	90
21	11	34	30	27	38	44	44	64	51	54

EXPERIMENT	DISCREPANCY								
NO.	0	1	2	3	4	5	6	≥7	≥9
17	2200	117	75	51	40	33	25	36	25
21	2196	74	60	54	58	43	35	45	38

Chi-Square = 50.28, d.f. = 18

TABLE C-15

MEAN ERROR (PRODUCTION)

EXPERI-MENT	DISCREPANCY									
NO.	≤-20	≤-10	≤-8	≤7	-6	-5	-4	-3	-2	-1
16	7	26	10	14	17	22	21	35	85	142
20	7	26	14	13	18	26	47	59	81	89

EXPERI-MENT	DISCREPANCY								
NO.	0	1	2	3	4	5	6	≥7	≥9
16	2278	151	63	48	20	12	14	21	14
20	2275	88	88	51	41	22	17	24	14

Chi-Square = 60.89, d.f. = 18

TABLE C-16

MEAN ERROR (PRODUCTION)

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	-8	-7	-6	-5	-4	-3	-2	-1
15	13	23	14	9	10	14	11	26	80	156
19	14	26	16	8	12	21	31	53	74	108

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7	≥9
15	2282	148	72	32	24	21	23	25	17
19	2274	103	75	47	39	29	24	29	17

Chi-Square = 45.87, d.f. = 18

TABLE C-17

RELIABILITY OF A KEYPUNCH

EXPERI-MENT NO.	DISCREPANCY							
	≤-20	≤-10	≤-6	≤5	-4	-3	-2	-1
4	7	15	16	15	43	69	129	139
31	12	15	5	12	22	44	84	133
32	12	16	13	12	40	68	112	166

EXPERI-MENT NO.	DISCREPANCY						
	0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
31	2377	146	71	47	16	11	5
32	2167	154	114	51	45	19	11

Chi-Square = 91.39, d.f. = 28

TABLE C-18

RELIABILITY OF TRANSCRIPTION (SAMPLE PHASE)

EXPERI-MENT NO.	DISCREPANCY ≤-10	≤-6	-5	-4	-3	-2	-1
4	22	16	15	43	69	129	139
35	35	9	16	46	62	100	124
36	18	9	16	42	64	133	153

EXPERI-MENT NO.	DISCREPANCY 0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
35	2237	146	97	61	35	21	11
36	2164	169	90	73	33	25	11

Chi-Square = 30.19, d.f. = 26

TABLE C-19

RELIABILITY OF COUNTING

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-6	-5	-4	-3	-2	-1
4	7	15	16	15	43	69	129	139
25	6	19	9	15	37	50	65	91
26	14	14	14	13	44	71	101	161

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
25	2441	89	63	60	29	17	9
26	2177	169	97	58	35	18	14

Chi-Square = 123.88, d.f. = 28

TABLE C-20

RELIABILITY OF COUNTING AND RECORDING

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-5	-4	-3	-2	-1
4	7	15	31	43	69	129	139
27	12	18	8	27	34	97	140
28	10	22	32	39	72	132	156

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
27	2343	157	69	47	33	7	8
28	2129	153	109	72	43	16	15

Chi-Square = 84.09, d.f. = 26

TABLE C-21

RELIABILITY BASED ON INVENTORY SIZE

EXPERIMENT NO.	DISCREPANCY ≤-20	≤-10	≤-6	-5	-4	-3	-2	-1
4	7	15	16	15	43	69	129	139
29	7	15	16	15	43	69	129	139
30	6	21	9	20	44	80	121	159

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	≥6
4	2148	166	109	72	41	15	16
29	2149	166	109	72	41	15	15
30	2122	143	102	74	26	17	56

Chi-Square = 53.05, d.f. = 28

TABLE C-22

RELIABILITY OF PULLING A BIN CARD

EXPERIMENT NO.	DISCREPANCY ≤-6	-5	-4	-3	-2	-1
4	38	15	43	69	129	139
33	8	15	43	70	129	139
34	154	18	43	53	111	164

EXPERIMENT NO.	DISCREPANCY 0	1	2	3	4	5	6	≥7
4	2148	166	109	72	41	15	10	6
33	2172	168	111	72	42	15	10	6
34	2081	156	93	64	36	16	7	4

Chi-Square = 192.97, d.f. = 26

A RELIABILITY MODEL OF AN INVENTORY SYSTEM

by

MICHAEL DUANE CHATHAM

AN ABSTRACT OF A MASTER'S THESIS

Submitted in partial fullfillment of the

requirements for the degree

MASTER OF SCIENCE

Department of Industrial Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

1977

ABSTRACT

This thesis is concerned with inventory errors. It is concerned with the type, frequency, and effect of human error on the on-hand inventory record. The purpose of this is to predict what the discrepancies between the physical and on-hand inventory should be under random error conditions. With this information control limits can be established for inventory error.

A FORTRAN simulation program is used to simulate the effect of inventory errors in both the on-hand and the recorded inventories. Reliability estimates were obtained for human operations from various sources including the American Institute for Research (AIR) Data Store. The reliability estimates and the simulation are used to produce distributions of discrepancies between the physical and the recorded inventories. Stochastic inequalities are then applied to the distributions to establish control limits for random error in the system.

It was found through the use of chi-square contingency analysis and linear regression that nearly all the variables describing the inventory system were significant. Though nearly all the variables were significant control limits were established which are relatively constant for all experiments where the number of part numbers was relatively constant.