A MODEL FOR ESTIMATING THE NUMBER OF RESIDUAL

ERRORS IN COBOL PROGRAMS
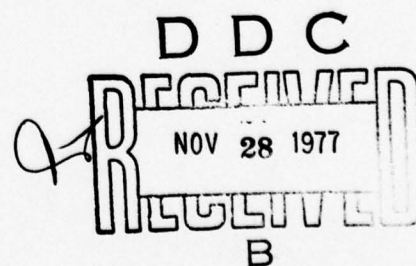
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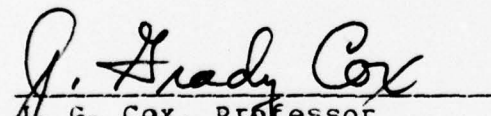
A MODEL FOR ESTIMATING THE NUMBER OF RESIDUAL

ERRORS IN COBOL PROGRAMS

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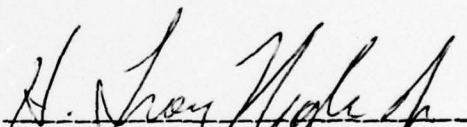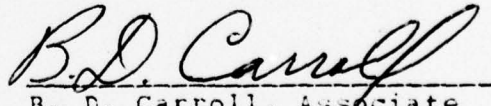DISSERTATION ABSTRACT

A MODEL FOR ESTIMATING THE NUMBER OF RESIDUAL
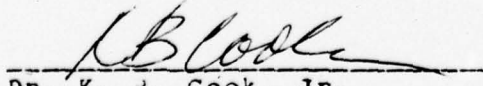
ERRORS IN COBOL PROGRAMS

Cecil E Martin

Doctor of Philosophy, June 7, 1977
(M.S., Georgia Tech, 1968)
(B. S., Georgia Southern College, 1963)

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The most significant problem facing the computer
profession today is manifested in two major complaints about
software: it is too expensive and unreliable. Most comput-
er professionals recognize the high cost as largely a symp-
tom of the latter complaint. The high incidence of errors
in software is the underlying reason for unreliability.

The number of errors uncovered during the software life
cycle has a significant impact upon the cost in terms of re-
sources (personnel and computer) needed to correct the er-
rors. The correction cost is a function of when, in the
software life cycle, an error is found. Software errors
found during the development phase generally cost less to
correct than errors which occur during the operations phase.
Therefore, it is necessary to detect software (program) er-
rors as early as possible--preferably before the software is

iv

made operational. Also, it is necessary to predict the number of residual errors in a program to determine if and when the program goes operational.

Program structural characteristics metrics (internal complexity) is a means of estimating the number of errors. Thirteen unrelated characteristics metrics are used to define 7 local complexities--control flow, input/output, data handling, computational structural design, interface, and data use--which are predictors of the number of errors in COBOL programs. Linear models for each of these metrics are available for predicting software errors.

Models developed from these metrics can be used to predict the number of errors in COBOL programs. The "best" single variable model for predicting errors is the Control Flow Complexity metric model. The "best" multiple variable model for predicting errors is the one that contains all 7 local complexity metrics. The latter model can be used when dealing with many types of programs that are developed by different organizations. However, each organization should estimate the model parameters relative to error data from its development projects.

ACKNOWLEDGEMENTS

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I. INTRODUCTION

The primary consideration in any system is that it per-
forms properly whenever the user wants to use it. For com-
puter systems, consisting of hardware, software and man-
machine interfaces, the most widely accepted and meaningful
measure of performance is total system reliability. Total
system reliability is defined as the probability that every
subsystem performs as intended for the necessary time and
under the conditions of customer use. Thus, there is an ob-
vious need to measure the reliability of the software sub-
system as well as the hardware and the man-machine subsys-
tems. But the most significant problem facing the computer
profession today is a software problem that is manifested in
two major complaints: software is too expensive and soft-
ware is unreliable. Most software professionals recognize
the former problem as largely a symptom of the latter. Al-
though this paper's main focus is primarily on the problem
of unreliable software, the problem of high cost is an
indirect issue because of its relationship to unreliability.
Therefore, to put the problem of unreliability into proper
perspective, the problem of high cost will be discussed
briefly. This discussion will stress the important role
that reliability plays in increasing the cost.

1

The High Cost of Software

There are several reasons why software is so expensive. The rest of this section will discuss a few of them.

Computer systems are becoming more complex as faster and more versatile hardware evolves. The resultant sophisticated uses of the computer systems demand that programmers develop reliable software to drive the computer system. Additionally, the man-machine interface which is generally handled by software is becoming more and more sophisticated. Consequently, software is becoming more and more complex because of the hardware and the man-machine interface subsystems. This increases software development cost.

As we continue to automate processes which control our life-style--bank accounts, air traffic control, medical systems, and defense systems--we have to trust more and more in the reliable functioning of software. Nowhere is this more evident than in the military where computers are being used increasingly as the heart of sophisticated weapon systems such as the B-1 bomber or a real-time command and control system. They control their environments by receiving data, processing it and returning results fast enough to affect the functioning of their environments. Reliable functioning of software is also critical in an on-line banking system where a software error (failure) may result in a loss of thousands of dollars. To develop reliable software, we

spend more and more resources on quality control during software development, thus, increasing the cost directly.

Software is a big business in the U. S. today. The annual cost of software is approximately 20 billion dollars. Its rate of growth is greater than that of the economy in general. Compared to the cost of hardware, the cost of software--development and maintenance--is escalating along the lines in Figure 1 [1]. Studies [2,3] indicate that software demand over the years 1975-1985 will grow about 21-23 percent per year. This is considerably faster than the growth rate in software supply at the current estimated growth rates of the labor force and its productivity per individual which has a combined growth rate of about 11.5-17 percent. Because of the demand and a shortage of experienced programmers, error prone software will be developed. Poor software reliability will be revealed by an excessive number of software errors resulting in higher maintenance cost and customer dissatisfaction.

Errors discovered after the software is operational will impact greatly upon the cost of software because of computer resources and manpower needed to correct the errors. About 70 percent of today's software dollar goes into software maintenance, and this number will likely grow [4]. This percentage varies by organization. Maintenance cost versus development cost for different organizations is depicted in Figure 2 [5]. DeRose [6] estimates that it costs the Department of Defense $75 an instruction to devel-
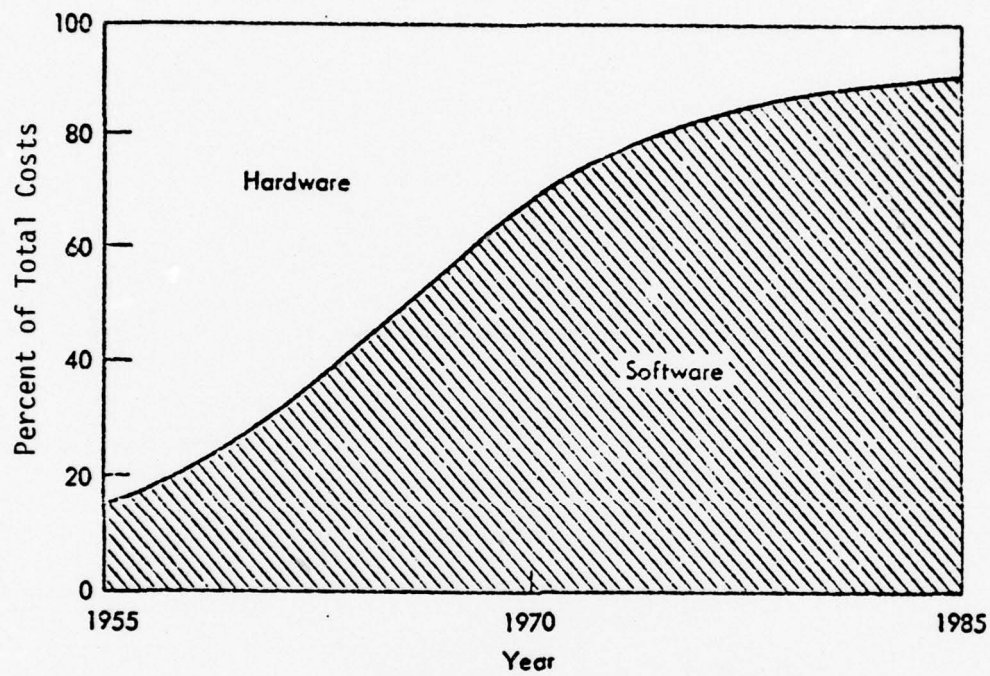
Figure 1. Hardware/Software Cost Trends.

```
+---------------------+--------+---------+--------+---------+---------+
|Organization         |        Maintenance           Development    |
|                     |                                              |
|------------------   |                                              |
|                     |                                              |
| General Tel.        |----------------------------------------------|
| and Electric        |...............................///////////////|
|                     |----------------------------------------------|
|                     |                                              |
| USAF Command        |----------------------------------------------|
| and Control 1       |...................................///////////|
|                     |----------------------------------------------|
|                     |                                              |
| USAF Command        |----------------------------------------------|
| and Control 2       |......................................////////|
|                     |----------------------------------------------|
|                     |                                              |
|                     |----------------------------------------------|
| General Motors      |........................................//////|
|                     |----------------------------------------------|
|                     |                                              |
+---------------------+--------+---------+--------+---------+---------+
                      0       25        50       75        100
                      Percent of 10-Year Life-cycle Costs
```
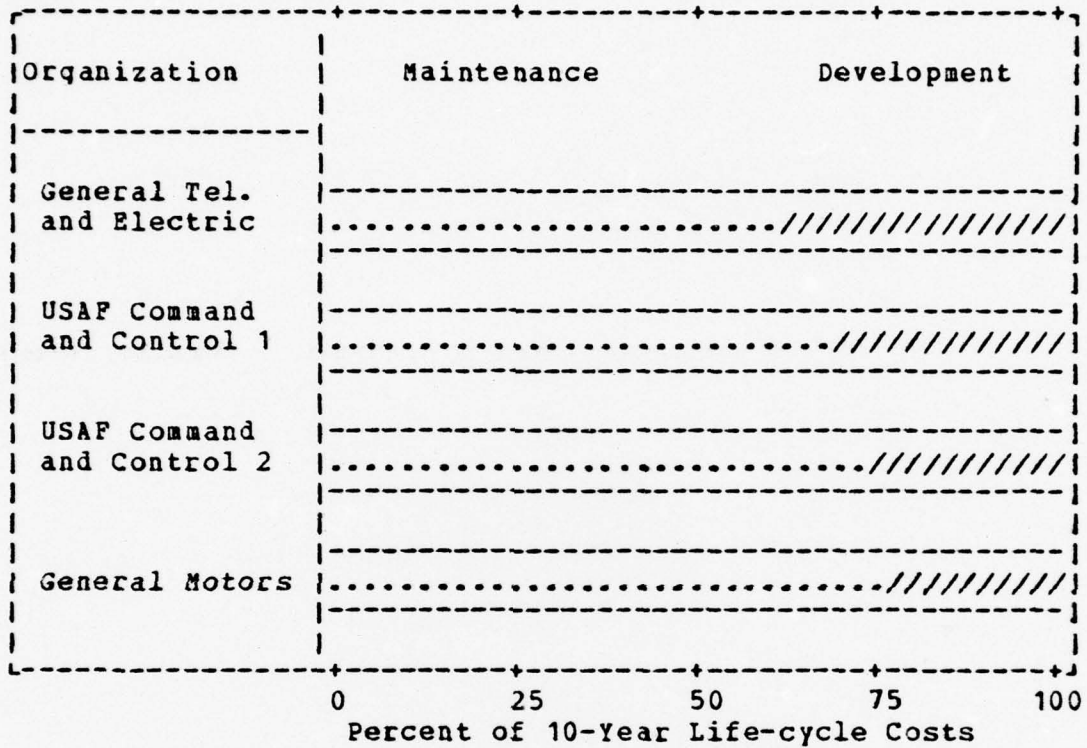
Figure 2   Life-cycle Cost Breakdown.

op aviation software, but that the maintenance cost is a lot more. On one particular aircraft computer, maintenance cost ran as high as $4000/instruction [7].

Proposed solutions to the cost problem invariably involve an attempt to raise programmer productivity by devising tools and techniques to allow programmers to work more quickly. But it should be obvious that the high cost of software is largely due to reliability problems. Cost is not usually lowered significantly by increasing programmer productivity if the latter is a measure of the speed of designing and coding the program. Depending on the situation, attempts to increase programmer productivity can increase cost. The best way to sharply decrease software cost is to reduce maintenance and testing cost by devising techniques to produce reliable software. This is the primary motivation for a software reliability theory. The next section will discuss the software reliability problem.

The Software Reliability Problem

Definition

Software reliability is the probability that a given program operates correctly, without an error, for some time period on the machine for which it was designed. Correctly means that the program performs as the ultimate user wants it to.

The Problem

The high incidence of errors in software is the underlying problem of software reliability. It would be fortunate if the well-developed theory of hardware reliability (see Appendix A) could be used to predict or enhance the reliability of software. Unfortunately, this is not the case since hardware reliability theory is based mainly upon the statistical analysis of random and wear-out failures of components with age. In contrast software is not subject to wearout failures once it is debugged.

There are other important differences between hardware and software which make the hardware reliability techniques difficult to apply to software. The elementary components of software are instructions. They do not wear, break, or deteriorate. All software errors are in some sense design or implementation errors [3] which are comparable to burn-in errors in hardware. When errors are found, they can be corrected and are no longer present in the program. In general, programs are more complex than corresponding hardware logic. Large programs are probably the most complex objects built by man. Some of them have millions of instructions. The complexity of these programs is so great that it is not well understood what the program can or can not do. Finally, there is a lack of a scientific basis for understanding the nature of programs. In contrast, the scientific basis of most hardware elements is well known.

Purpose

Figure 3 shows a summary of current experience on the relative cost of correcting software errors as a function of the software life cycle phase in which they are corrected [5]. For obvious reasons, it is desirable to predict the number of errors in a software system at the earliest moment in the software life cycle (development and operational phases). Unfortunately there is no proven technique in practice today.

The research done to date suggests the hypothesis that profiles of actual program characteristics (internal complexity) are good predictors of the number of errors in a program. This paper will present the results of an analysis of error data to determine if actual program characteristics are predictors of the number of errors, propose a model for predicting the number of errors in COBOL programs, and discuss the application of this model to software reliability. The rest of this Chapter and Chapter II and III contain background information only. The reader is directed to continue reading this report at Chapter IV if he is already familiar with software engineering and software reliability concepts.

Survey of Related Research

Over the past ten years, several investigations in the area of software reliability and phenomenology have been undertaken. As a result of these investigations, reliabili-
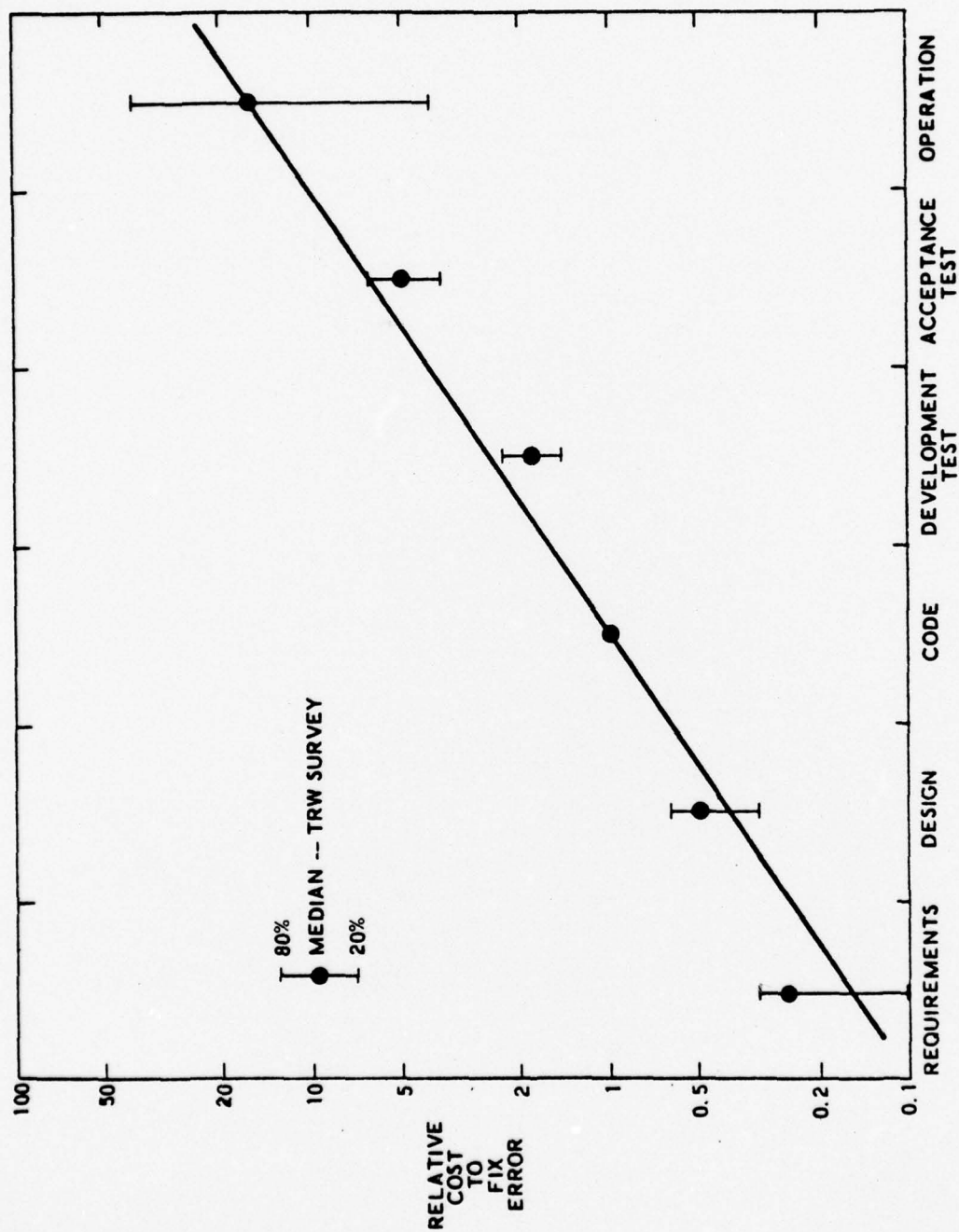
Figure 3. The Price of Procrastination

ty models which attempt to describe the failure of software
have been proposed and discussed. These models were derived
from hardware reliability and have not been very successful
. This failure is primarily founded on two reasons.

One, there are fundamental differences between software
phenomenology and the hardware-oriented assumptions on which
the models were based. The failure mechanism of a hardware
component is by chance or by component wear-out whereas the
failure mechanism of a program is a function of the number
of remaining errors in the program.

Two, the fundamental statistical issues which emanate
from the use of these models have, by and large, been
ignored. These issues pertain to model verification, the
development of a procedure which formalizes the testing and
debugging of software, and parameter estimation. In partic-
ular, the success of the models depends largely on the
estimation of the original number (N) of errors in software
and the constant of proportionality (K) used in determining
failure rate. Of the several methods used, the method of
maximum likelihood gives the most reasonable estimators for
N and K [8-10]. However, this method does not yield satis-
factory results [10].

Models are being developed which explain previous error
histories in terms of appropriate program phenomenology.
These models are based on a view of a program as a mapping
from a space of inputs into a space of outputs; of program
operation as the processing of a sequence of points in the

input space, distributed according to an operational pro-
file; and of testing as a sample of points from the input
space, [11,12] (see Figure 4). This approach can be used
conceptually as a means of appropriately conditioning time-
driven reliability models [5]. But, we still are not able
to truly estimate the number of errors in software.

Additional insights into reliability estimation have
come from analyzing the software errors relative to actual
characteristics of programs. Currently, it seems that a
measure of program complexity offers the best estimator for
the number of residual errors in a program. Akiyama [13]
concludes that the number of program errors is strongly cor-
related to the number of conditions plus the number of calls
to other programs rather than program size. Lipow and
Thayer [14] suggests the interesting hypothesis that the
number of program errors can be best predicted by a measure
of the internal complexity of programs. They, using empiri-
cal data, concluded that the number of software errors found
in programs written in JOVIAL could be predicted by the num-
ber of branches, a measure of program internal complexity.
Herndon and Lane [15] developed an approach to the quantifi-
cation of software errors as a function of module complexi-
ty. Module complexity is based upon module composition.
The complexity measure was shown to be a useful managerial

MINIMUM-VARIANCE UNBIASED ESTIMATOR

- PICK N (SAY, 1000) RANDOM, REPRESENTATIVE INPUTS

- PROCESS THE 1000 INPUTS, OBTAIN M (SAY, 3) FAILURES

- THEN R = PROB (NO FAILURE NEXT RUN) = $\dfrac{N - M}{N}$ = 0.997
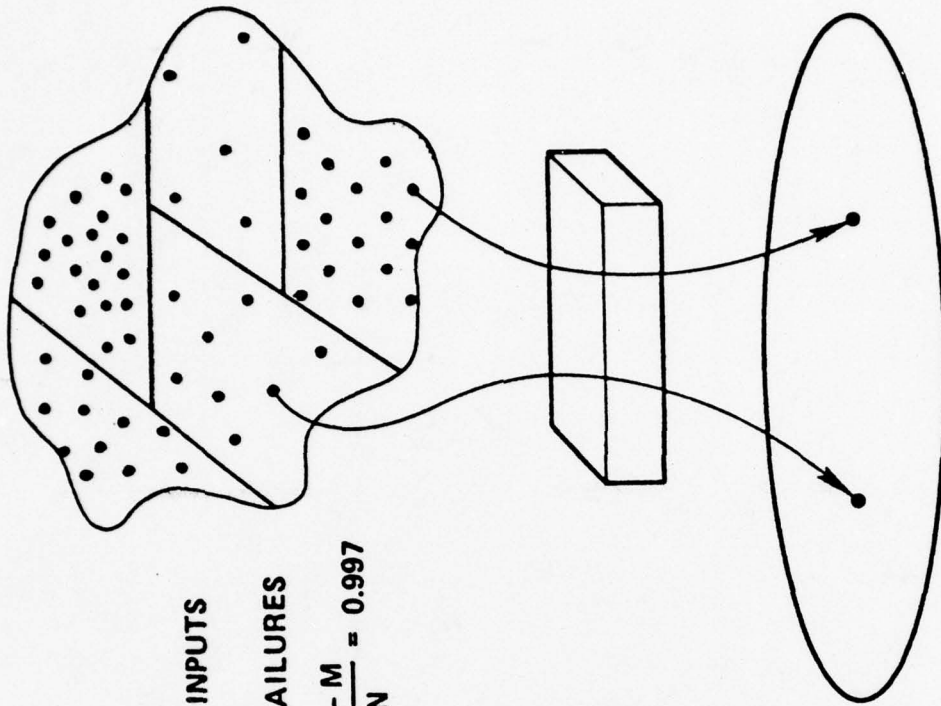
Figure 4. Input Space Sampling Provides a Basis for

Software Reliability Measurement

tool. Program components with high complexity indicators
should receive more attention than ones with low complexity
indicators.

There have been several other investigations into pro-
gram complexity that did not address the error problem.
These are briefly summarized below. Flynn [16] suggests
that the number of nodes in the smallest path-isomorpnic
program scheme may be a useful measure of inherent program
complexity. Sullivan [17] proposes several complexity
measures--c1, c2, c3, p1 and p2. The c1, c2 and c3 measures
deal with control flow graphs of programs. The p1 and p2
measures deal with data flow graphs of programs. This re-
port basically concludes that the number of conditions plus
1 is a complexity measure of the control flow of a program.
McCabe [18] develops a graph-theoretic complexity measure--
the number of conditions in a program plus 1. He illus-
trates how it can be used to manage and control program com-
plexity. Additionally, he proves that complexity is inde-
pendent of program size. It is appropriate at this point to
stress that most all of the software reliability models
employ the program size. This may be one of the reasons why
the models have not been very successful in modeling the
failure rate of programs.

II. SOFTWARE ENGINEERING CONCEPTS

Introduction

The TERM "software engineering" was made popular by two NATO conferences in 1968 and 1969 [23,24]. Since then the development of software has evolved into an engineering discipline involving a multiplicity of specialized branches--Requirements Engineering, Theory of Program Structures, Programming Methodology, Software Reliability, Software Project Management, etc. This chapter will briefly discuss those concepts relative to estimating the number of residual errors in programs.

It is perhaps best to view this chapter as an attempt to identify the underlying concepts of software engineering in a form that permits the main issues of this paper to be better understood.

Definitions

Software includes not only computer programs, but also the associated documentation required to develop, operate, and maintain programs. The generation of timely documentation is an integral part of the software development process [5,25].

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Software Engineering is the practical application of
scientific knowledge in the design and construction of com-
puter programs and the associated documentation required to
develop, operate, and maintain them. This definition covers
the entire software life cycle (see Figure 5), thus includ-
ing redesign and modification activities which are often
called "software maintenance" [5].

The Goals of Software Engineering

There are four fundamental goals of software engineer-
ing: modifiability, efficiency, reliability, and understand-
ability [26]. Boehm [27] provides a larger list which he
calls characteristics of software quality (Figure 6). In
what follows, this paper addresses some of these important
goals, those considered basic in nature.

Modifiability implies controlled changes in which some
parts are unchanged while others are altered, all in such a
way that a desired result is obtained. Modifiability is
difficult to achieve because changes occur for many reasons.
For example, when transferring software to a new computer
or operating system, it is desirable to keep invariant the
logical effects of the system, limiting changes only to nec-
essary machine-dependent aspects. Changes are also required
to add new capabilities, correct errors in the program, and
improve software performance. Different approaches are nec-
essary to satisfy these different types of modifiability
[26].
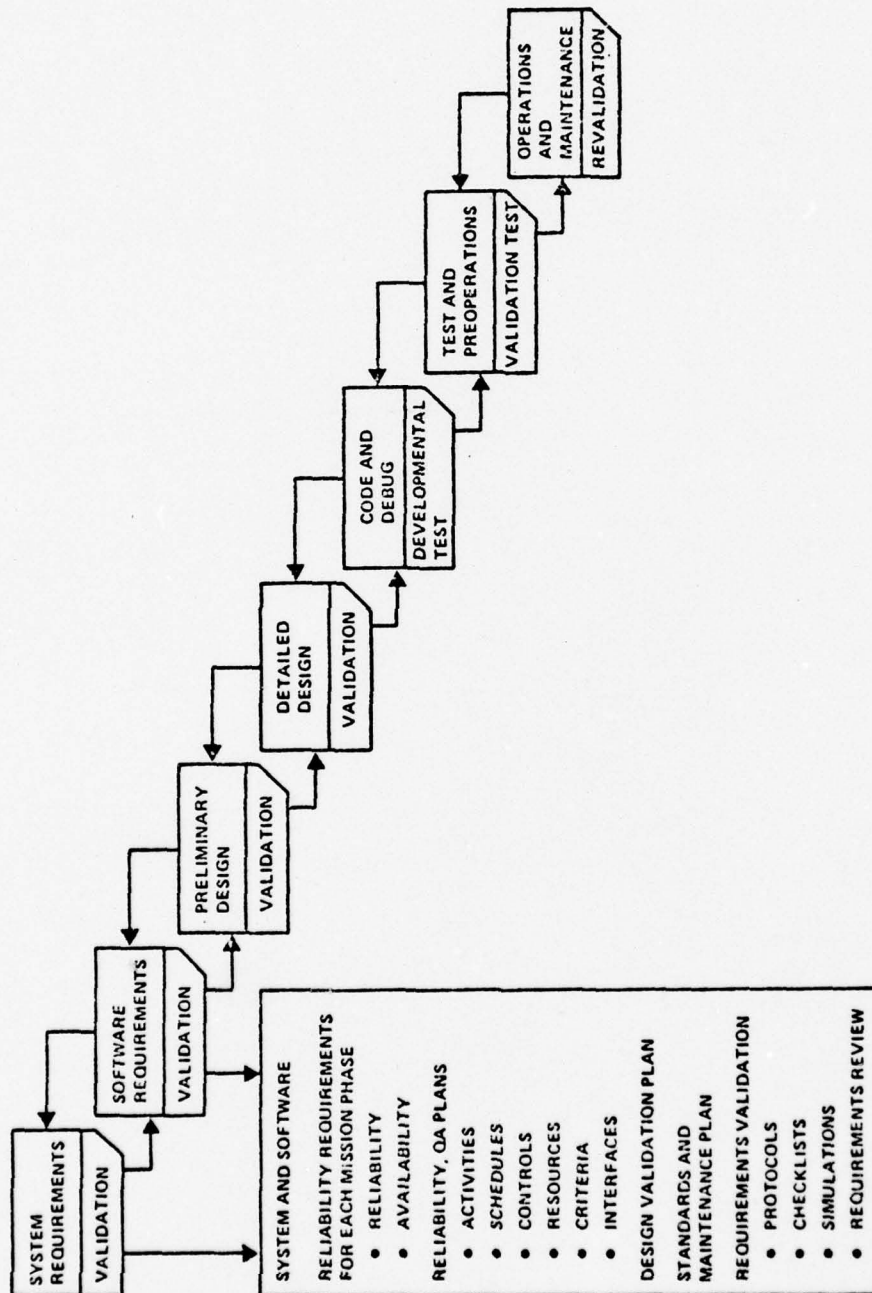
Figure 5. Software Reliability Oriented Life Cycle Plan
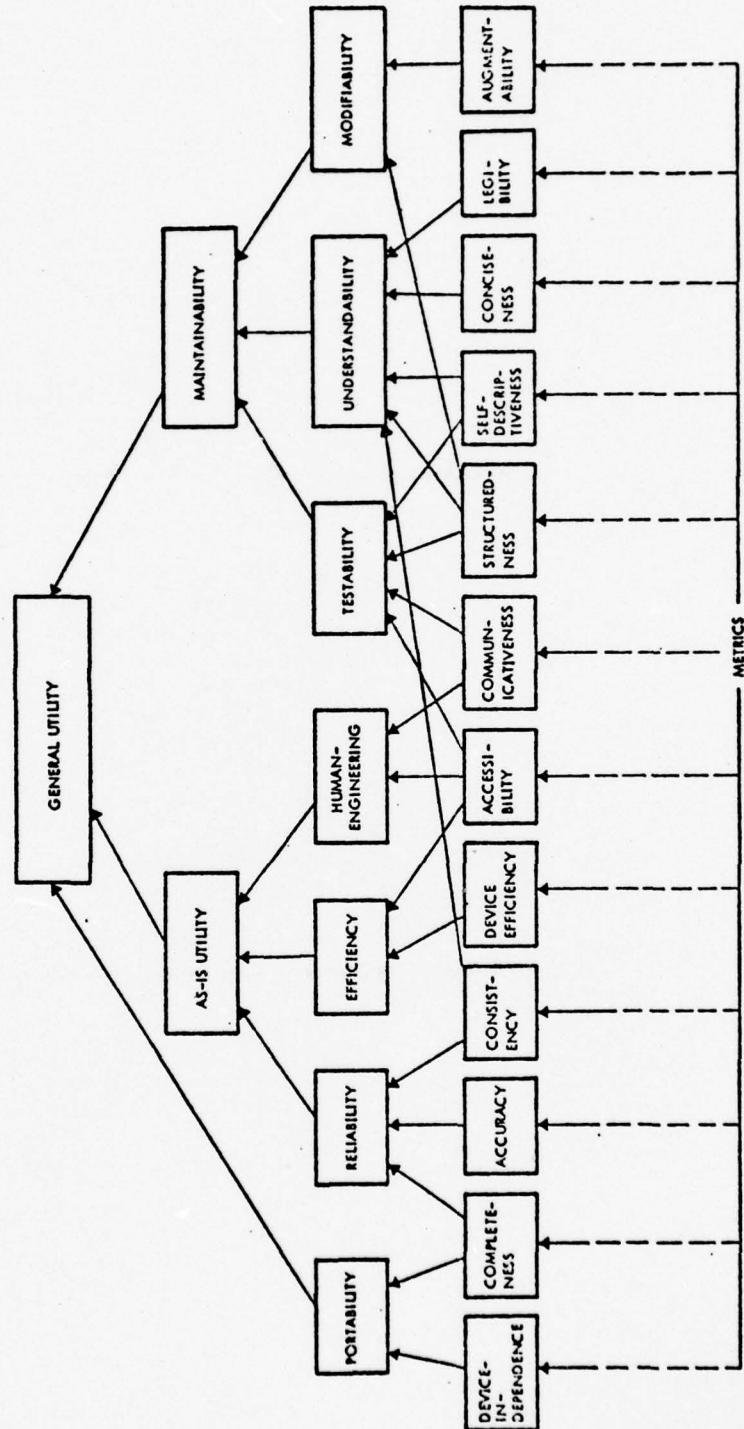
Figure 6. Characteristics Tree.

Additionally, modifiability implies not only the ability to have an adaptable evolutionary design, employ standardized software building-blocks, tune for performance, etc., but also the ability to maintain project schedules and budgets. There has been much progress in achieving this goal within the past ten years.

Efficiency, defined as the optimal use of computer resources by a program, is a much abused goal. Primarily this is because it is prematurely assigned a high priority in engineering tradeoffs. Efficiency should be treated within the context of other issues. For example, achieving modifiability can provide the basis for meeting efficiency goals during the maintenance phase of the software life cycle. In addition, insights reflecting a more unified understanding of a problem have more impact on efficiency (via abstraction and uniformity) than any amount of "bit twiddling" within a faulty structure. In general, the efficiency goal does not dominate, as reliability and modifiability, the practice of software engineering [26].

Reliability is an important goal which is much in vogue today. Reliability is concerned with conception, design, and construction as well as failure in operation or performance. Unlike efficiency which is often prematurely applied, reliability is more often considered too late in the software life cycle. Since reliability can only be built in at the beginning of the development cycle--it cannot be an add-on at the end--it is a primary problem to be solved in any

software system. Hence, reliability has a crucial effect on software engineering practices [26]. Because of its importance, Chapter III will be devoted entirely to it.

Understandability is the final basic goal which exerts a strong influence in all aspects of software engineering. In particular, it is not a property of legality. It is, therefore, much more important since the entire conceptual structure is involved [26,27]. Also, in any circumstance an acceptable level of understandability either is or is not present. Thus, there is no middle ground. Although understandability is a prerequisite to reliability and modifiability, it also draws attention to an important barrier to it--complexity [26]. Management of complexity is a crucial part of software engineering methods, and the need to manage complexity arises from the goal of understandability. The only way to achieve understandability relative to an inherently complex system is to impose an appropriate structure and organization on the software system. As such, the structure must be represented in a clear notion that permits the different translations (requirements, design, source coding, object coding, and documentation) to bridge the gap between the actual system and an understandable representation of it. Thus, achieving understandability depends as much upon the software engineering tools such as compilers as on the methods such as structured programming [26].

Other goals such as portability and testability are of lesser importance than the ones discussed above. Boehm [27,28] discusses all of the above goals as characteristics of quality software.

The Principles of Software Engineering

The principles of software engineering are modularity, abstraction, localization, hiding, uniformity, completeness, and confirmability. These principles are applied in various combinations throughout the fundamental software life cycle (see Figure 4) to achieve the desired goals discussed above [5,25].

The decomposition of a system [29] depicts the programs or modules of the system organized into a structure by the relationships (interfaces) among them. The seven principles, singly and in combination, are used to determine and control those relationships [26]. They are used as decision criteria to ensure that the resulting decomposition attains the goals of the software system. Thus, each principle deals with some aspect of the relationships-i.e., the interfaces among the modules or programs. The rest of this section discusses each principle separately.

Modularity deals with the properties of a hierarchical software structure. It has been given various definitions by several authors [30-36]. Basically modularity deals with how the structure of an object can make the attainment of some purpose easier. In essence, modularity is purposeful

structuring [29]. Therefore, the principle of modularity is made concrete by explaining how certain constraints on the structure of systems can make it easier or harder to achieve some goal such as modifiability, efficiency or reliability.

Imposing constraints on structures is the essence of applying the modularity principle in software engineering [26]. For example, top-down structured programming [36] which forces programmers to make explicit the conditions under which programs are designed and coded can help ensure understandability and prevent errors [26].

It may be possible for a given program to satisfy all goals simultaneously. A program may have one structure if modules are constructed according to one rule (module strength) and a different structure if a different rule (module coupling) is considered [4,37].

<u>Abstraction</u> is a very pervasive principle [34,21]. Despite the existence of the above papers, no practical definition of abstraction exists. However, most researchers in this field agree that the essence of abstraction is to extract essential properties while omitting nonessential details. Hierarchical decomposition in the form of levels shows abstraction in its best form. Each level of the decomposition shows an abstract view of the lower levels purely in the sense that details are subordinated to the lower levels [26]. The top level expresses the program in

terms natural to the originator of the task while lower
levels express commitments to specific ways of realizing the
terms of the higher levels [39].

When combined with the principle of completeness, ab-
straction ensures that a given level in a decomposition is
understandable as a unit without requiring either knowledge
of the lower levels of detail, or necessarily how it partic-
ipates in the system as viewed from a higher level. As
such, this principle is employed on the one hand to obtain a
description of some level of the system which could be real-
ized by any of several implementations, and on the other
hand to give a description of one part of a system which
could be used in many other systems requiring the same com-
ponent at that level of abstraction.

Abstraction interacts strongly with the purpose
underlying any particular decomposition. Unless it is com-
bined with the principle of modularity, abstraction is of
little practical value. When employed to achieve the goal
of understandability, each decomposition level while
presenting more and more detailed views of the system must
do so in terms that are understandable to the intended user
[26].

Localization is concerned with physical proximity.
Things must be brought together in one place. Thus, the
localization principle deals with physical interfaces,
textual sequence, memory, etc. The other principles can
interrelate the localized things to serve specific purposes.

Logical and physical records as well as paged memories are examples of localization. Also the avoidance of GOTO's in structured programming is an application of localization to control structures which simplifies confirmability and enhances understandability [26].

The Hiding principle, as discussed by Parnas [29], is used as the major criterion for a decomposition into modules. Although it is not the same, it is related to the idea of postponing binding decisions in top-down programming. The purpose of hiding is to make visible only those properties of a module needed to interface with other modules and to make inaccessable details that should not affect other parts of a system. Abstraction assists in identifying details that should be hidden. Basically, hiding is concerned with access constraints [29].

Uniformity is also an important principle. Since it ensures consistency, it is an obvious principle to apply in software engineering. It is applied to notational matters to yield notation (documentation) that is free of confusing and perhaps costly inconsistencies. When conbined with the abstraction principle, uniformity implies a notation that permits arbitrary mechanization of the internal detailing of an object (the notation does not constrain one's choice of implementation). Also, when the hiding principle is added, the result is a notation that does not permit several implementation choices and also ensures that no unnecessary details of specific implementaion are revealed by the nota-

24

tion. Basically, uniformity is the lack of inconsistencies and unnecessary differences [26].

Completeness is another obviously important principle. This principle ensures that all the essentials of an abstraction are explicit and that nothing essential is left out. Every detail does not have to be shown, but the set of abstract concepts must cover every detail.

When completeness is applied to notational matters, it requires that a notation provides a means for saying everything that one wants to say. When it is combined with abstraction, completeness implies that a notation should be concise, permitting the suppression of invariant details in favor of highlighting the changeable details. Additionally, completeness, when combined with uniformity and abstraction and applied to the goal of efficiency, allows programmers to select different implementation mechanisms to tune a system's performance without having to change the form of any subroutine call [26].

Confirmability is a principle that ensures that information needed to verify correctness has been explicitly stated. This information is used for finding out whether stated goals such as reliability have been achieved.

> "Applied to design issues, confirmability re-
> fers to the structuring of a system so it is
> readily tested. It must be possible to stim-
> ulate the constructed system in a controlled
> manner so its response can be evaluated for
> correctness. Applied to notational matters,
> confirmability means that a notation should
> require explicit specification of constraints
> that affect the correctness of a design or im-

plementation (e.g., data declarations that
specify range of values and units of value
as well as mode of representation). Applied
to the practice of software engineering, con-
firmability refers to the use of such methods
as structured walk-throughs of design, egoless
programming [38], and other methods that help
to ensure that nothing has been overlooked." [26].

Software Metrics

The result of effective software engineering is the
production of a program that meets the requirements
(assuming the requirements are accurately stated) of the
user. But, how can software be measured so it can be
compaired against specified goals of the user? Currently,
measures of software attributes seem to be an answer.

The term "metric" by definition means a standard of
measure. A software metric is defined as a measure of the
extent or degree to which software possesses and exhibits a
certain property or attribute [27,28,40]. Software metrics
is discussed briefly in the following paragraphs. Chapter
IV will concentrate on the metrics applied to COBOL source
code as a measure of program composition.

It seems obvious that the software profession is at the
point of moving from a handicraft into an engineering indus-
try. There have been enough large failures in software pro-
jects to motivate us to acquire full control over the soft-
ware technology. To be successful and have full control, we
must be able to recognize and measure all critical factors,
and not simply the easily available ones, such as space and
time consumption. Software metrics is concerned with meas-

uring all factors, simple and critical, related to software.
In particular, measures relating to the use of human talent
resources are of major interest because of its scarcity
today, compared to the relatively cheap machine resources.
Also, measures related to reliability are becoming more and
more important as computers are increasingly used for cru-
cial functions [40]. There are many other software metrics
(see Figure 6) such as maintainability, portability, under-
standability, etc., but this paper is concerned with measur-
ing one characteristic--internal complexity of COBOL pro-
grams. These metrics will be discussed in detail in chapter
4.

Summary

There are many aspects of software engineering. The
intent of this chapter has been to focus the underlying
goals and principles of software engineering into a coherent
framework for the readers of this paper. Software metrics
is applied to determine to what degree a certain attribute
is present in software.

III. SOFTWARE RELIABILITY CONCEPTS

What is Software Reliability?

The most significant problem facing the software pro-
fessional today is unreliable software. This is the reason
for recent emphasis on developing a software reliability
theory. As previously defined, software reliability is the
probability that a given program operates correctly, without
an error, for some time period on the machine for which it
was designed. Software reliability is thus a function of
the number of errors in a program.

Reliability is not an inherent property of a program;
it is largely related to how the program was designed, con-
structed, tested, and operated. The word probability in
the definition actually represents the probability that
there are no errors in the program given a valid input from
its input space. At times it is simply used as a qualita-
tive measure of the lack of errors in a program [4].

Reliability as a Measure of Software Quality

To provide a meaningful assessment of software quality,
quantitative methods of evaluating software are being devel-
oped. Until recently, quality assessments have been subjec-
tive evaluations of software based on program deficiencies.

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However, subjective evaluations for software are not consistent with the use of the methodologies used to measure the quality of hardware. For complex computer systems, consisting of hardware, software, and human interface subsystems, the most meaningful measure of quality is total system reliability. As such, the most meaningful measure of software quality is the reliability of the software subsystem. If software reliability is not explicitly stated it must be determined from the specification of the total system. A study of the total system reliability and cost-benefit trade-offs will determine the reliability apportionment among the hardware, software and human operated subsystems [41].

What is an Error?

Although software reliability is the most appropriate measure of software quality, there are terminology problems because the meanings of such words as software failure and software errors are not entirely obvious by analogy with the corresponding hardware reliability concepts which are well defined. A software error is present when an input is made or a command is given and the program does not respond as the user expects it to. A failure is an occurrence of an error. A failure may be manifested in many ways. A complete stoppage of the program may or may not occur.

Detection of failures is, to a large extent, a subjective decision which must be made by the users or the test

personnel. Hopefully, this decision will be made on the
basis of objective criteria such as performance specifica-
tions. In actual practice, failure detection depends on a
user's observation of an error, so, in effect, a software
failure is what a user says is an error.

After failures are detected a programmer must analyze
the program and locate the causes of the failure. Basically
all errors are design or implementation errors. Logical or
clerical errors in coding may be found to be responsible for
producing the incorrect results. Also the program specifi-
cation could be in error. When errors are located, action
is taken to correct the errors to prevent recurrence of the
failures. The correspondence between software errors un-
covered and software failures detected is not necessarily
one-to-one. Many errors may occur without a failure being
detected, and a failure may be a result of several errors.
Also, a software failure may be reported that is in fact no
software failure at all, but rather a user or hardware defi-
ciency.

Failures differ with respect to their impact on the
mission of the software. Severe failures may result in a
failure of a mission, while less severe failures may only
cause aggravations or limitations which have little effect
on the overall mission of the total system.

The reader, if he has written a large program, should
now be able to grasp the elusive nature of software reli-
ability. Software errors are not an inherent property of

software. Errors are basically human mistakes and we can
never expect to find them all--regardless of how well we
test the programs. But, we can measure or predict the num-
ber of residual errors so we can decide when the software
has reached an acceptable reliability level.

Do Software Failures Occur Randomly with Time?

Unlike hardware, there is no physical mechanism which
generates software failures. When all errors are removed,
the software is 100 per cent reliable and will remain so
forever, provided no program changes are made. What then
accounts for the randomness of software failures?

Different input combinations result in a different re-
sponse from the software. The paths traversed within a
software program depend on the input combinations. Each
path can be thought of as containing possible software er-
rors waiting to be discovered. Without correction, the same
errors will occur each time the same logic path is executed.
If the errors result in an observable software failure,
the given failure can be reproduced at will, or it can be
avoided by user control of the input combinations. There-
fore, software failures are functions of the input
combinations--not random functions of time. However, in
reality, input combinations are chosen in a somewhat random
fashion, and the resultant effect is that errors are un-
covered and failures are observed at random. It is with

this meaning that we talk about the random occurrence of software failures [41].

Reliability Models

The most important unknown of software reliability is the number of residual errors in a program. If an estimate of this number were available during the testing stages it would help determine when to stop testing. Also if we knew the number of remaining errors in an operational program we could estimate the cost of maintenance and establish a level of confidence in the program. Other related attributes for which estimates are desirable are the reliability of the program and the mean-time-to-failure of the program. Measures of the program's complexity would be useful to estimate the number of errors and to judge the quality of the design. If software reliability models were available that would model software failures, then one could deal with the unknowns of software reliability [4].

There are 3 types of software reliability models being evolved today. A number of software reliability models are discussed in references [42-47]. These models are closely related to hardware reliability theory and contain significant assumptions about the underlying probability distribution of software failures. References [48-56] are reliability studies which contain evaluations of these models relative to specific error data. These models seem to apply only to specific situations and do not have general applica-

tion in any environment. The next set of models, discussed in references [11,57-59], produce similar results, but are not based on hardware reliability theory. The last set of models is concerned with predicting the complexity of a program [14-22]. The rest of this chapter will discuss the hazard function for software failures.

Hazard Function for Software Failures

We shall assume that a large program is resident in a computer and is servicing a steady stream of dissimilar "inputs". We shall assume that these inputs enter the program at arbitrary points in time, and that each such entry can be looked upon as an opportunity to detect an error in the program. Thus, we assume that software errors are detected in a random manner.

Software does not age with time, therefore, it is reasonable to assume that its failure rate is constant between points in time at which changes are made. Every time an error is detected, we eliminate it. If we ignore the possibility of introducing new errors then our failure rate is a step function as indicated in Figure 7. Several variations and justifications for this model have appeared in the literature. For the purpose of this paper, it will suffice to illustrate that a program failure rate is decreasing and will eventually go to zero, assuming there are no modifications for new capabilities. This is in contrast to the hazard function of a hardware component (see Figure 8).

```
          |
          |
          |
          |
       |K(N)___,
Failure |       |
Rate    |       |
        |      L_K(N-1)___,
        |               |
        |               L_K(N-2)___,
        |                        |
        |                        L___...
        |
        |
        L_____+_____+_____>
              x(1)      x(2)            x(3)

                      Time
```
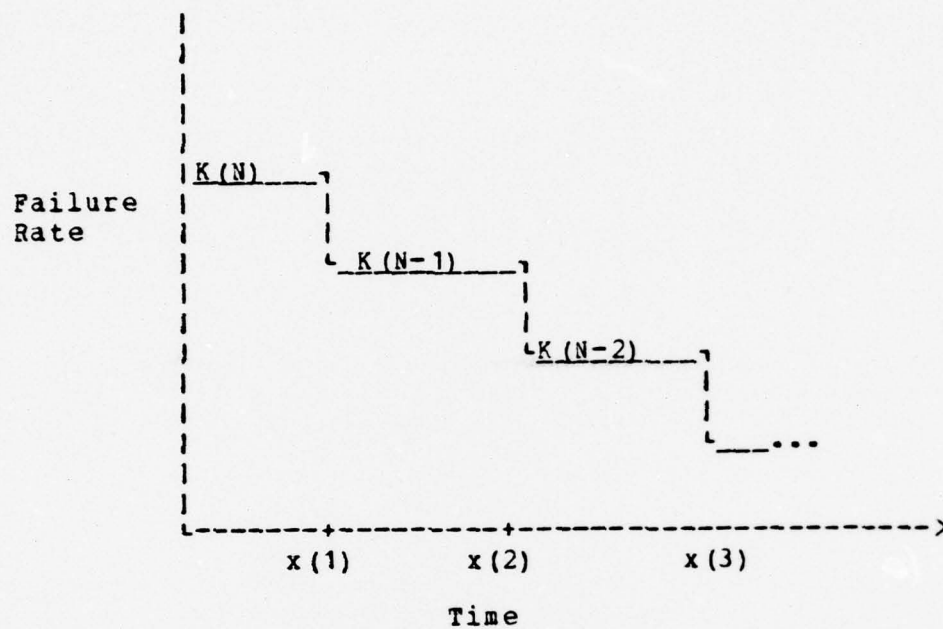
Figure 7. Failure Rate Changes As Errors Are Removed
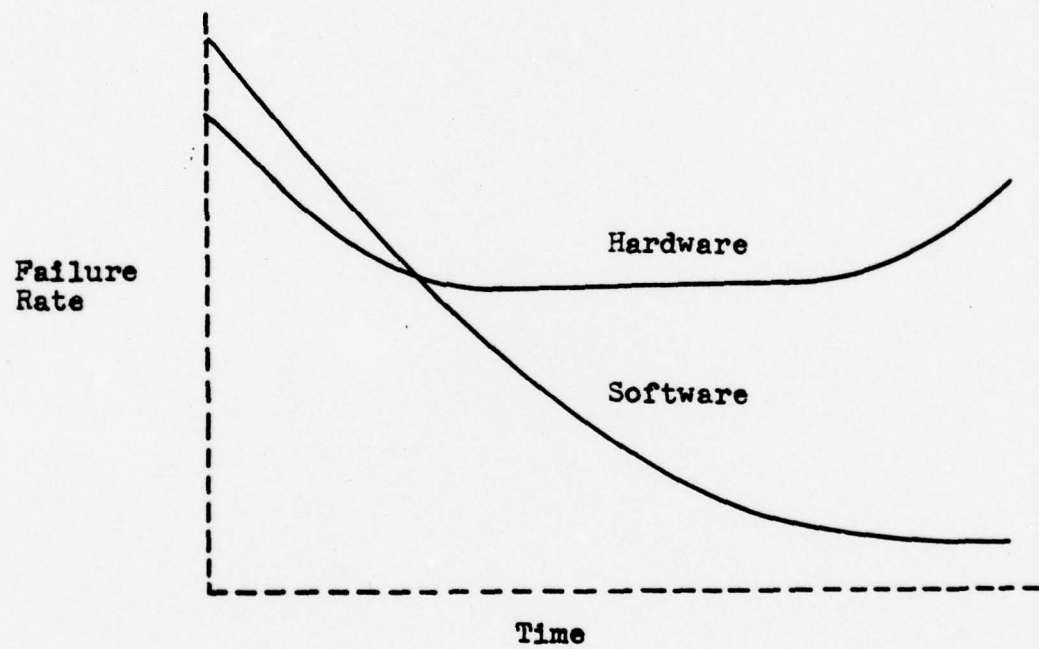
Figure 8. Hardware vs. Software Failure Curves

At the start of the testing process, we assume that the program contains an unknown number of errors, say N. The failure rate is assumed to be proportional to the residual number of errors in the program. Every time an error is encountered, the error is removed and no new error is introduced. Although these assumptions make the model less than realistic, Jelinski and Moranda [42] have demonstrated the usefulness of a model of this type in analyzing error data from the U.S. Navy and the Apollo program of NASA.

Let $x(1)$, $x(2)$, ... , denote the points in time at which software errors are detected and corrected. Then, according to the assumptions of the model, the failure rate between $x(i-1)$ and $x(i)$ is $K(N-i+1)$, $i = 1,2, ... , n$, for $n \leq N$, where K is the constant of proportionality. The failure rate generated by the testing process is illustrated in Figure 7. If $T(i)$ denotes the time interval between $x(i-1)$ and $x(i)$, then from the assumption that time-to-failure is exponentially distributed

$$F[t(i)] = P[T(i) \leq t(i)] = 1 - \exp[-K(N-i+1)t(i)], \quad K > 0,$$

and $t(i) \geq 0$.

If K and N were known, then the reliability of the software prior to testing, the distribution function of the time to test, the number of errors to be removed in order to obtain a desired level of reliability, and other such information can easily be determined. In practice, K and N are unknown, and hence the estimation of K and N becomes critical.

In order to estimate K and N, and to obtain a stopping rule for testing the program, one must use t(1), t(2), ... , t(n) as the realizations of T(1), T(2), ... , T(n), for n ≤ N. This estimation problem is an unusual one. The time intervals t(1), t(2), ... , t(n), do not constitute a random sample of size n from a single failure distribution, but rather n samples, each of size 1, from n different but related distributions [10]. Therein lies the problem of predicting K and N.

Schneidewind [60,61] showed that error data fitted no single underlying probability distribution. This is more reason to believe that failure functions are not only functions of the remaining errors but also the composition of the program itself.

The remaining chapters of this paper will be devoted to developing and discussing a model for estimating the number of errors in COBOL programs.

IV. DESCRIPTION OF DATA

Introduction

Error data processing involves three interrelated activities: collection, classification into error categories, and analysis. Since collection and classification have been dealt with adequately in other sources [61-67] [50] [56], analysis is the primary concern of this paper. While analysis has been the primary concern of this research, the other two were considered by using concepts and techniques developed in other studies.

The purpose of this chapter is to describe data that are used to develop a model for predicting the number of errors in COBOL programs. Chapter V will present a detailed analysis of the data described in this chapter.

Terminology Revisited

Although defined elsewhere, several terms need clarification to familarize the reader with what follows in the rest of this paper.

The term software reliability, for the purpose of the analysis of empirical data, needs to be redefined. Software posseses reliability to the extent that it is expected to perform its intended functions satisfactorily. With this in

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mind, errors in programs represent an inability of the pro-
grams to perform intended functions satisfactorily. An
error-free program would be a reliable program. Henceforth
in this paper, anything that causes software not to perform
its intended function is an error. Specifically, the term
error is a user dissatisfaction, which is documented on a
form, with the results of a program. The error may not nec-
essarily be the result of an execution of a program, e.g.,
design reviews can result in the detection of errors.

The term project is the combination of development ac-
tivities required to produce the software and its documenta-
tion. Three sources of data are used in this report. Be-
cause of the restrictions in employing the actual system and
program names, the data sources are called Project 1, Pro-
ject 2, and Project 3. Each one will be discussed later.

Project Descriptions

The three projects represent small to large software
development activities. The application software for all
three projects is written in COBOL. The smallest compilable
unit of source code is the program. Each project is dis-
cussed below. Table 1 lists the data available from each
project.

Project 1

Project 1 is a data collection system [67] consisting
of 5 batch programs with a total of 2280 lines of code.
The system provides an on-going data base for input into re-

TABLE 1. Data Availability for Each Project

		Project 1	Project 2	Project 3
1)	General Project Descriptions	X	X	X
2)	Design Problem Data	X	X	
3)	Problem Report (Error) Data	X	X	X
4)	Software Characteristics	X	X	X
5)	Testing Data	X	X	
6)	Computer Usage Data	X	X	

liability models. The data base also contains program characteristics as discussed in this paper. The system applies to COBOL programs designed to execute on the Honeywell H6060 computer system throughout the Air Force. The 5 programs in this system utilize a file management system available on the H6060.

Project 2

Project 2 is an on-line system involving several kinds of data processing activities such as personnel management, accounting and finance, inventory etc. Only 14 programs are available for analysis. There are 19045 lines of source code in these programs. These programs execute on the National Cash Register NCR8200 computer system.

Project 3

Project 3 represents an initial delivery of a large on-line Command Manpower Data System(CMDS). CMDS is a resource accounting and management information system which supports the Manpower and Organization function at Major Command level throughout the Air Force. Data for 46 programs are available for analysis. There are 54116 lines of source code in these programs. These programs execute on the H6060 computer system and perform a wide variety of data processing activities, general purpose utility, data retrieval, data maintenance, etc.

Approach to Data Collection and Classification

It would be ideal to perform a study of this nature
using the same collection and classification tools and pro-
cedures for all projects. Since real data from on-going
projects within different organizations are being used, this
was not possible. Data sources are the normal data
collection and classification system of the organization
developing the software. For example, the Air Force Data
System Design Center(AFDSCC) has a manual system for
collecting error reports. Project 3 data was recorded using
this system.

Although the data is reasonably good, it is obvious
that it is not the same type of data from all projects.
This presented a problem when trying to classify an error
according to a specific category. Finally it was decided to
work only with actual errors that required a change in
source code to affect corrective action. By considering
only code change errors and performing analysis at the indi-
vidual program level, it was possible to generate similiar
data from all projects. Errors were classified into 12 cat-
egories. These categories are:

1) Computationa,

2) Logic,

3) Data Input,

4) Data Handling,

5) Data Output,

6) Interface,

7) Array Processing,

8) Data Base,

9) Operation,

10) Program Execution,

11) Documentation, and

12) Other

The categories along with types of errors in each category are presented in Table 2.

Software Characteristics

Boehm [27] presents a detailed discussion of characteristics of software quality (see Figure 6). Thayer and Lipow [50] discuss the two forms of software quality characteristics, those that can be quantitatively measured and those that require some subjective evaluation. Both are needed to explain errors. Both forms were considered by Thayer and Lipow and examples are presented in Table 3. The subjective form did not show much promise as predictor variables for the number of errors in programs. Since previous research showed that software structure influenced the number of errors and since our primary objective is to develop a complexity model for predicting the number of errors in COBOL programs, this paper is concerned with only structural characteristics. Only those that can be measured are considered in this report.

TABLE 2.   Error Categories

COMPUTATIONAL ERRORS

Incorrect operand in equation
Incorrect use of parenthesis
Sign convention error
Units or data conversion error
Computation produces an over/under flow
Incorrect/inaccurate equation used
Precision loss due to mixed mode
Missing computation
Rounding or truncation error

LOGIC ERRORS

Incorrect operand in logical expression
Logic activities out of sequence
Wrong variable being checked
Missing logic or condition tests
Too many/few statements in loop
Loop iterated incorrect number of times
(including endless loop)
Duplicate logic

DATA INPUT ERRORS

Invalid input read from correct data file
Input read from incorrect data file
Incorrect input format
Incorrect format statement referenced
End of file encountered prematurely
End of file missing

DATA HANDLING ERRORS

Data file not rewound before reading
Data initialization not done
Data initialization done improperly
Variable used as a flag or index not set properly
Variable referred to by the wrong name
Bit manipulation done incorrectly
Incorrect variable type
Data packing/unpacking error
Sort error

TABLE 2. Error Categories (Continued)

DATA OUTPUT ERRORS

Data written on wrong file
Data written according to the wrong format statement
Data written in wrong format
Data written with wrong carriage control
Incomplete or missing output
Output field size too small
Line count or page eject problem
Output garbled or misleading

INTERFACE ERRORS

Wrong subroutine called
Call to subroutine not made or made in wrong place
Subroutine arguments not consistent in type, units,
order, etc.
Subroutine called is nonexistent
Software/data base interface error
Software user interface error
Software/software interface error

ARRAY PROCESSING ERRORS

Data not properly defined/dimensioned
Data referenced out of bounds
Data being referenced at incorrect location
Data pointers not incremented properly

DATA BASE ERRORS

Data not initialized in data base
Data initialized to incorrect value
Data units are incorrect

OPERATION ERRORS

Operating system error (vendor supplied)
Hardware error
Operator error
Test execution error
User misunderstanding/error
Configuration control error

PROGRAM EXECUTION ERROR

Bad object code

TABLE 2. Error Categories (Continued)

DOCUMENTATION ERRORS

User manual
Interface specification
Design specification
Requirements specification
Test documentation

OTHER

Time limit exceeded
Core storage limit exceeded
Output line limit exceeded
Compilation error
Code or design inefficient/not necessary
User/programmer requested enhancement
Design nonresponsive to requirements
Code delivery or redelivery
Software not compatible with project standing

TABLE 3. Available Parameters

<u>Program Structural Characteristics</u>

Program size

Total source code statements
Executable statements
Non-executable statements
Machine dependent number of instructions
  (ENTER SYMBOLIC)

Number of unconditional branches

Number of conditions in program

Number of direct interfaces

With routines within program and other application
  programs
With operating system

Number of arguments in interface calls

Data interfaces

Number of global data blocks
Number of internal data variables

Number of procedures

Number of entry points

Number of exit points

Routine code type

Number of computational
Number of logical
Number of data handling
Number of I/O

Loop and nesting levels

Pages of documentation

TABLE 3. Available Parameters (Continued)

Computer time (clock time, _not_ CPU time)

Development time
Test time

Subjective Characteristics

Routine difficulty at preliminary design

Routine difficulty after formal test and delivery

Design
Code
Debug/checkout
Implementation
Documentation

Routine type

Executive
Control
Setup
Input
Computational
Post processing
Output

Personnel data

Number of people working on routine
Load factor on each programmer
Programmer rating
Programmer/job evaluation

Structural Characteristics

Program structural characteristics are measurable. They quantify the actual physical attributes of a program. The application of metrics allows the quantification of such things as a program's size, input/output patterns, use of a data base, computations performed, interfaces, use of the various language elements, and logical complexity [17,18].

The approach taken was to provide as much quantative detail as possible. In an effort to tie specific error categories to types of code within a program, 22 generic types of structural characteristics were chosen as language metrics. The structural characteristics chosen for this study are presented in Table 4. Please note that a measure for each error category is included. The purpose for choosing these characteristics is to measure the likelihood that a program may have particular kinds of errors. These characterisitcs will also be useful in future studies of error type distributions. Since there were no automated tools available to collect structure data, a program was developed by the author to analyze COBOL source code. This program is called COBOL Characteristics Analyzer Program(CCA). It was originally designed for the NCR8200 computer system, and has been converted to run on the H6060 computer.

TABLE 4.   STRUCTURAL CHARACTERISTICS DEFINITIONS

Metric Variable	Definitions
LC	Number of logical conditions
IO	Number of input/output statements
CO	Number of arithmetic statements
DH	Number of data transfer statements
PC	Number of CALLS to external and internal routines
UBR	Number of unconditional branches
EXIT	Number of EXIT statements
STOP	Number of STOP statements
OSC	Number of CALLS to operating system
CC	Number of CALLS to compiler to COPY source code from the library
TS	Total statements = NEX + NNEX
NEX	Number of executable statements
NNEX	Number of non-executable statements
FD	Number of file descriptions
RD	Number of record descriptions or "01" level descriptions
DD	Number of data item descriptions
TD	Total descriptions = FD + RD + DD
DR	Number of data references
NCO	Number of comments

TABLE 4.   STRUCTURAL CHARACTERISTICS DEFINITIONS
continued

Metric Variable	Definitions
PAR	Number of paragraphs
NL	Number of source lines There can be more than one statement per line.
RW	Number of references to "reserved" words

COBOL Characteristics Analyzer Program

CCA is a utility program which statistically analyzes COBOL source. It breaks a program's code into its language elements. This analysis is done at the program level; however, it identifies interfaces between routines, between the subject program and other application programs, and between the subject program and the operating system. Table 4 has presented the list of metrics chosen to quantify the structural characteristics of COBOL programs. CCA computes the values for these metrics. Figure 9 presents sample output for a program called S-PTUO.

Please note that the columns PERCENT OF TOTAL and PERCENT OF EXECUTABLE (see Figure 9) require special interpretation. For example, the number of logical is 80. This is not the number of logical statements in the program, it represents the number of logical conditions in the program.

DATE: 01 25, 1977   VERSION DATE: 01 25,1977

PROGRAM CHARACTERISTICS SUMMARY
FOR
S-PTU0

TOTAL STATEMENTS= 1168   NUMBER EXECUTABLE STATEMENTS= 566   NUMBER NON EXECUTABLE STATEMENTS= 602

NUMBER FILE DESCR= 6   NUMBER OF RECORD DESCRIPTIONS= 34   NUMBER OF DATA ITEM DESCRIPTIONS= 536

TOTAL DECLARATIONS= 576   NUMBER OF DATA REFERENCES= 4447   NUMBER OF COMMENTS= 613

NUMBER PARAGRAPHS= 60   NUMBER OF LINES= 2040   NUMBER RESERVE WORDS= 562

STATEMENT PROFILES	NUMBER	PERCENT OF TOTAL	PERCENT OF EXECUTABLE
LOGICAL	80	4.84	14.13
INPUT/OUTPUT	185	15.83	32.68
COMPUTATIONAL	118	10.10	20.84
DATA HANDLING	100	8.56	17.66
PROCEDURE CALLS	27	2.31	4.77
UNCONDITIONAL BRANCHES	139	11.90	24.55
EXIT	12	1.02	2.12
STOP	3	.25	.53
OPERATING SYSTEM CALLS			
COMPILER CALLS	15	1.28	2.65

Figure 9. Example Output from CCA.

Each AND and OR is counted as a logical condition. Because of this the PERCENT columns will not add to 100 percent.

Summary of Available Data for Each Project

Individual project data is summarized in Tables 5-7 respectively. Tables 8-10 contain descriptive statistics for individual project data. The error data were collected from software discrepancy reports provided by project programmers. Program CCA was used to collect the structural characteristics data. This data is analyzed in the next chapter. When, in the course of analysis, specific project data are germane to results, the reader is encouraged to refer back to the corresponding data.

TABLE 5. PROJECT ONE DATA

METRIC VARIABLES BY PROGRAM

Program No.	Total No. Of Errors (N)	LC	I/O	CO	DH	PC	UBR	EXIT	STOP	OSC	CC	TS	NEX	NNEX	FD	RU	DD	TD	DR	NCO	PAR	NL	RW
1	25	43	32	15	74	15	26	12	2	15	4	556	223	333	5	21	174	200	581	0	43	641	217
2	13	23	7	7	6	5	12	3	1	7	2	95	62	33	1	2	28	31	152	0	12	117	45
3	68	119	20	26	146	16	67	12	1	5	0	598	396	202	4	25	131	160	896	2	42	597	373
4	15	18	16	8	29	12	18	10	1	3	0	183	103	80	5	7	62	74	255	16	27	254	107
5	58	77	31	55	131	18	56	10	1	4	4	619	369	250	5	29	208	242	990	32	36	673	450

TABLE 6. PROJECT TWO DATA

METRIC VARIABLES BY PROGRAM

Program No.	Total No. Of Errors (N)	LC	I/O	CO	DH	PC	UBR	EXIT	STOP	OSC	CC	TS	NEX	NNEX	FD	RD	DD	TD	DR	NCO	PAR	NL	RW
1	12	21	36	51	94	16	13	7	1	0	0	423	219	204	3	25	161	197	1560	49	24	544	286
2	9	18	29	0	20	7	22	1	1	0	0	114	80	34	2	9	17	28	484	25	7	176	76
3	17	34	103	25	126	10	30	5	1	0	0	664	302	362	6	30	308	345	2350	250	23	1053	361
4	22	59	57	53	124	18	59	9	1	0	0	519	317	202	5	26	159	190	1206	109	22	723	326
5	5	9	18	1	21	2	3	0	1	0	0	92	52	40	3	5	22	30	102	37	8	154	45
6	0	2	16	5	20	2	3	1	1	0	0	127	48	79	3	7	60	70	94	43	8	206	40
7	5	11	80	5	81	30	37	11	1	0	0	661	206	455	9	51	349	409	1128	265	25	1051	204
8	9	26	57	16	57	17	24	10	1	0	0	286	174	112	5	16	77	98	1100	115	23	498	224
9	4	11	65	8	27	5	26	4	1	0	0	377	123	254	5	16	216	237	681	114	14	584	113
10	84	255	238	36	548	182	642	70	2	0	3	2125	1420	705	4	58	629	691	7641	642	256	3566	1660
11	58	180	167	139	341	72	69	47	1	0	3	1898	912	986	5	50	915	970	6062	575	76	2740	1047
12	32	103	111	51	289	132	62	26	1	0	0	2345	621	1724	4	118	1592	1714	3853	353	58	3012	806
13	45	80	185	118	100	27	139	12	3	0	15	1168	566	602	6	34	536	576	4447	613	62	2040	562
14	20	36	169	21	492	25	63	71	2	0	0	2028	810	1218	5	134	1063	1202	4466	516	44	2688	741

TABLE 7. PROJECT THREE DATA

METRIC VARIABLES BY PROGRAMS

Program No.	Total No. Of Errors (N)	LC	I/O	CO	DH	PC	UBR	EXIT	STOP	OSC	CC	TS	NEX	NREX	FD	RD	DD	TD	DR	NCO	PAR	NL	RW
1	25	512	202	114	409	134	386	31	1	25	2	3392	1896	1496	8	139	1253	1400	3825	17	228	3421	2220
2	21	119	139	38	193	46	140	17	0	12	2	1384	698	636	9	71	558	633	1388	11	106	1494	799
3	18	3	12	0	0	6	0	1	0	2	0	52	27	25	3	5	7	15	47	0	6	89	25
4	24	433	76	47	405	175	234	14	1	55	2	1020	1442	378	8	37	291	336	3165	6	130	1624	1557
5	3	27	38	16	73	11	30	4	1	8	2	467	215	272	2	25	151	173	490	1	24	511	263
6	5	33	39	16	81	11	32	4	1	9	2	502	228	272	2	25	153	190	533	1	24	529	239
7	8	157	12	57	165	28	53	3	1	33	2	747	511	236	2	46	181	229	1163	2	33	676	534
8	23	733	48	116	686	155	194	15	1	79	3	3290	2030	1260	2	112	1131	1249	4731	29	119	2925	2144
9	4	59	40	13	86	25	17	1	1	4	0	635	246	309	2	39	302	343	639	0	22	649	209
10	2	18	36	4	47	14	8	4	1	9	0	419	141	278	2	28	224	254	357	0	28	457	166
11	1	3	12	1	14	3	2	0	0	7	0	125	45	80	1	12	59	72	107	0	7	155	57
12	67	1584	54	233	1314	330	1012	20	1	41	2	5323	4599	724	5	46	656	787	11533	45	373	4100	3305
13	5	92	13	26	195	68	59	3	1	4	2	777	463	314	2	27	272	331	1025	9	44	771	345
14	3	15	18	13	28	8	10	3	0	4	0	187	68	119	3	9	104	116	143	3	12	246	56
15	5	81	77	13	191	42	75	2	0	1	2	902	404	418	4	45	336	385	966	3	41	855	437
16	3	59	58	11	59	17	36	4	0	18	4	534	269	265	6	48	193	247	622	20	29	699	294
17	24	597	145	104	440	79	480	18	1	27	2	2402	1893	509	10	56	415	481	4090	122	205	2645	1990
18	30	749	81	59	926	901	417	76	1	22	0	4009	3322	639	6	62	574	642	7872	0	432	3107	1756
19	19	227	74	35	266	60	133	11	1	91	2	1287	900	397	5	29	341	375	2169	16	92	1253	653

TABLE 7. PROJECT THREE DATA
Continued

METRIC VARIABLES BY PROGRAMS

Program No.	Total No. Of Errors (N)	LC	I/O	CO	DH	PC	UBR	EXIT	STOP	OSC	CC	TS	NEX	NNEX	FD	RD	DD	TD	DR	NCO	PAR	NL	RW
20	12	193	117	18	125	19	92	5	1	11	2	881	563	319	6	38	242	236	1439	0	44	832	676
21	17	227	195	91	365	70	173	18	1	49	2	1675	1191	484	4	40	460	452	2953	34	151	1730	1274
22	5	94	87	48	145	54	46	8	1	9	2	732	494	238	3	29	186	218	1520	0	61	731	437
23	3	57	54	13	105	30	33	2	1	8	2	448	305	143	3	17	110	130	789	0	36	431	321
24	4	82	48	19	136	46	66	4	1	14	2	603	418	185	3	26	139	168	1181	47	63	744	436
25	6	132	150	40	272	45	74	3	2	11	2	980	731	257	4	29	207	240	2180	0	74	969	794
26	7	132	150																2173				
27	16	104	87	66	260	43	66	4	2	11	2	907	645	262	4	30	207	241	1919	1	72	932	303
28	8	74	90	16	245	10	69	6	1	25	2	1073	538	535	14	43	420	432	1293	53	43	1253	523
29	14	263	123	41	357	77	217	20	1	14	2	1638	1120	516	8	42	442	490	2840	38	147	1995	1675
30	15	129	103	32	449	81	86	8	1	11	2	1655	902	753	5	49	664	718	2161	139	36	1961	913
31	9	141	88	25	262	35	96	8	2	23	2	1272	675	597	3	35	532	570	1456	104	62	1435	1000
32	5	62	12	6	69	12	43	4	1	48	2	405	259	146	4	18	111	133	635	30	24	489	339
33	13	149	51	5	369	64	39	7	1	8	2	1405	745	660	8	41	572	621	1602	211	63	1622	814
34	7	67	65	10	146	9	43	4	1	21	3	709	368	341	4	35	277	316	1126	74	46	927	644
35	15	223	80	39	363	50	163	11	1	33	2	144	942	502	4	32	447	493	2080	19	95	1488	811
36	8	121	80	77	476	77	195	6	1	6	2	1630	1041	589	4	46	499	549	2319	1	164	1842	1297
37	11	163	36	36	197	39	102	10	1	37	2	915	623	292	3	41	215	264	1693	39	97	1055	643
38	22	258	48	50	356	27	210	9	0	57	0	1195	1015	180	2	13	164	179	2275	6	93	1082	554

TABLE 7. PROJECT THREE DATA
Continued

METRIC VARIABLES BY PROGRAMS

Program No.	Total No. Of Errors (N)	LC	I/O	CO	DH	PC	UBR	EXIT	STOP	OSC	CC	TS	NEX	NNEX	FD	RD	DD	TD	DR	NCO	PAR	NL	RM
39	9	20	26	3	14	0	26	0	1	4	2	153	96	57	3	10	33	46	209	28	15	217	90
40	6	114	33	25	234	23	55	12	1	16	2	913	515	398	4	56	322	382	1382	26	49	977	502
41	2	29	41	15	87	16	18	6	1	9	2	416	224	192	3	20	152	175	577	41	34	534	237
42	1	15	18	3	3	12	4	1	1	25	2	137	84	53	1	4	44	49	279	0	9	173	76
43	5	54	21	15	97	18	43	3	2	20	2	432	275	157	2	15	122	139	633	1	28	448	272
44	12	222	41	20	261	20	194	2	1	49	2	1555	810	745	5	71	651	727	2080	20	83	1705	1240
45	18	13	30	14	105	25	40	1	1	0	0	514	289	225	3	17	193	213	702	0	35	555	335
46	4	86	42	31	116	26	82	9	1	30	2	640	425	215	4	29	167	200	912	2	77	735	415

TABLE 8. DESCRIPTIVE STATISTICS FOR PROJECT ONE DATA

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE	STD ERROR OF MEAN	SUM	VARIANCE
N	35.8000000	25.48921340	13.0000000	68.0000000	11.39912277	179.0000000	649.70000
LC	56.0000000	42.16633728	18.0000000	115.0000000	18.85735531	280.0000000	1778.00000
IQ	21.2000000	10.52140675	7.0000000	32.0000000	4.75531614	106.0000000	110.70000
CC	21.0000000	21.13054661	1.0000000	55.0000000	9.44986772	105.0000000	446.50000
CH	77.2000000	61.30008157	6.0000000	146.0000000	27.41422988	386.0000000	3757.70000
PC	13.2000000	5.06951674	5.0000000	18.0000000	2.26715681	66.0000000	25.70000
UBR	35.8000000	24.29403219	12.0000000	67.0000000	10.86462148	179.0000000	590.20000
EXIT	9.4000000	3.71483512	3.0000000	12.0000000	1.66132477	47.0000000	13.80000
STCP	1.2000000	0.44721360	1.0000000	2.0000000	0.20000000	6.0000000	0.20000
OSC	6.8000000	4.81663783	3.0000000	15.0000000	2.15436592	34.0000000	23.20000
CC	2.0000000	2.00000000	0.0000000	4.0000000	0.89442719	10.0000000	4.00000
TS	410.2000000	250.54680202	95.0000000	619.0000000	112.04793617	2051.0000000	62773.70000
NEX	230.6000000	151.06058387	62.0000000	396.0000000	67.55634685	1153.0000000	22819.30000
NNEX	179.6000000	122.88127795	33.0000000	333.0000000	54.95537256	898.0000000	15100.30000
FC	4.0000000	1.73205081	2.0000000	5.0000000	0.77459667	20.0000000	3.00000
RC	16.8000000	11.71324037	2.0000000	29.0000000	5.23832034	84.0000000	137.20000
CC	120.6000000	75.17845436	28.0000000	208.0000000	33.62082688	603.0000000	5651.80000
TC	141.4000000	87.50885669	31.0000000	242.0000000	39.13515044	707.0000000	7657.80000
DR	574.8000000	373.03846987	152.0000000	990.0000000	166.82787537	2874.0000000	139157.70000
NCC	10.0000000	14.02000000	0.0000000	32.0000000	6.26990034	50.0000000	196.00000
PAR	32.0000000	12.86468033	12.0000000	43.0000000	5.75325595	160.0000000	165.50000
NL	456.4000000	253.43598797	117.0000000	673.0000000	113.34001941	2282.0000000	64229.80000
RW	238.4000000	171.76961315	45.0000000	450.0000000	76.81770629	1192.0000000	29504.80000

TABLE 9. DESCRIPTIVE STATISTICS FOR PROJECT TWO DATA

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE	STC ERROR OF MEAN	SUM	VARIANCE
N	23.0000000	24.19154334	0.0000000	84.0000000	6.46546192	322.0000000	585.2308
LC	63.35714286	73.97151962	2.0000000	255.0000000	19.76372620	845.0000000	5471.7857
IC	95.07142857	69.91694445	16.0000000	238.0000000	18.66608940	1331.0000000	4888.3791
CC	37.78571429	42.96721214	0.0000000	139.0000000	11.46347648	529.0000000	1846.1813
CH	167.1428571	178.22218513	20.0000000	548.0000000	47.63204401	2343.0000000	31763.3626
PC	38.92857143	53.73794766	2.0000000	182.0000000	14.41552288	545.0000000	2909.3022
UBR	85.14285714	164.13917575	3.0000000	642.0000000	43.86874103	1192.0000000	26941.6703
EXIT	19.57142857	24.80916172	1.0000000	71.0000000	6.29527737	274.0000000	615.4945
STCP	1.285714294	0.61124985	1.0000000	3.0000000	0.16336339	18.0000000	0.3736
OSC	0.0000000	0.00000000	0.0000000	0.0000000	0.00000000	0.0000000	0.0000
CC	1.500000000	4.33351345	0.0000000	15.0000000	1.07400181	21.0000000	16.2692
TS	916.2142857	828.78049229	92.0000000	2345.0000000	221.50903364	12827.0000000	686877.1044
NEX	417.6571429	402.36605170	48.0000000	1420.0000000	107.53685608	5850.0000000	161898.4396
NNEX	464.3571429	505.11485474	34.0000000	1724.0000000	134.96762339	6977.0000000	255141.0165
FC	4.642857143	1.73680267	2.0000000	9.0000000	0.46418004	65.0000000	3.0165
RC	41.35714286	39.63605030	5.0000000	134.0000000	10.55918603	579.0000000	1571.0155
CC	436.0000000	468.06278343	17.0000000	1592.0000000	125.05904C79	6104.0000000	219082.7692
TC	482.6428571	504.22150369	28.0000000	1714.0000000	134.75896511	6757.0000000	254239.3242
CR	2512.428571	2384.84499462	94.0000000	7641.0000000	637.37663503	35174.0000000	5687485.6484
NCO	264.7142857	232.95144649	25.0000000	642.0000000	62.25889129	3706.0000000	54266.3736
PAR	46.28571429	64.05217653	7.0000000	256.0000000	17.11866425	648.0000000	4102.6813
NL	1360.357143	1193.18143614	154.0000000	3566.0000000	318.85115245	19045.0000000	1423661.9396
RW	398.9285714	436.03590725	40.0000000	1660.0000000	117.03002057	5585.0000000	191875.4560

TABLE 10. DESCRIPTIVE STATISTICS FOR PROJECT THREE DATA

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE	STD ERROR OF MEAN	SUM	VARIANCE
N	11.60869565	11.42021261	0.00000000	67.00000000	1.68381849	534.00000000	130.4213
LC	191.08695652	274.18329847	3.00000000	1584.00000000	40.42612187	8790.00000000	75176.4812
IC	66.30434783	47.53852887	12.00000000	202.00000000	7.00923267	3050.00000000	2259.9498
CC	37.02173913	41.74711654	0.00000000	233.00000000	6.15527653	1703.00000000	1742.8217
DM	250.45652174	245.88702675	0.00000000	1314.00000000	36.25406466	11521.00000000	60460.4314
PC	69.04347826	150.48336291	0.00000000	991.00000000	22.18756140	3176.00000000	22645.2425
UER	124.28260870	171.55946584	0.00000000	1012.00000000	25.29506383	5717.00000000	29432.6517
EXIT	9.67391334	13.10649432	0.00000000	76.00000000	1.93244716	445.00000000	171.7802
SICP	1.04347826	0.41933925	0.00000000	2.00000000	0.06182820	48.00000000	0.1758
GSC	21.91304348	20.42637303	0.00000000	91.00000000	3.01176440	1008.00000000	417.2367
CC	1.71739130	0.86056941	0.00000000	4.00000000	0.12688404	79.00000000	0.7406
TS	1165.32608696	1053.88871549	52.00000000	5323.00000000	155.38741378	53605.00000000	1110681.4246
NEX	771.76086957	849.20295139	27.00000000	4595.00000000	125.20814433	35501.00000000	721145.6527
NNEX	393.50000000	291.75512944	25.00000000	1496.00000000	43.01694700	18101.00000000	85121.0556
FC	6.04347826	11.43864118	1.00000000	80.00000000	1.68653563	278.00000000	130.8425
RC	37.28260870	25.19846825	3.00000000	135.00000000	3.71531145	1715.00000000	634.9628
CC	324.60869565	257.75470542	7.00000000	1253.00000000	38.00975565	14932.00000000	66458.1101
TC	367.15217391	281.30931709	45.00000000	1400.00000000	41.47679600	16889.00000000	79134.9319
CR	1854.58695652	2039.71842911	47.00000000	11533.00000000	300.74007519	85311.00000000	4160451.2700
NCC	26.10869565	42.75627479	0.00000000	211.00000000	6.30406879	1201.00000000	1828.0990
PAR	82.19565217	86.43457738	6.00000000	432.00000000	12.74414214	3781.00000000	7471.0053
NL	1176.43478261	908.66213382	85.00000000	4162.00000000	133.97492249	54116.00000000	825666.8734
RW	775.65217391	727.96682517	25.00000000	3465.00000000	107.33285272	35680.00000000	529935.6986

V. ERROR DATA ANALYSIS

Introduction

Error data analysis is important because of the
necessity to cope with problems of cost and software unreli-
ability. Examples of areas which benefit from error data
analysis include management of software development efforts,
design of software engineering techniques and tools, and
determining which software characteristics are relevant to
software reliability. This chapter is mainly concerned with
the latter. The principal emphasis of this analysis has
been on individual program error data collected during
testing and operational usage.

There are many kinds of data available from the soft-
ware life cycle (see Figure 5). Since the main emphasis of
this research stems from the idea that much can be said
about the quality and reliability of software from the soft-
ware's error history, only error data were analyzed. The
primary approach has been not to repeat other research, but
to verify and expand previous findings.

The purpose of this chapter is to summarize an analysis
of data collected from the three projects. This will be ac-
complished by presenting the results of an empirical and

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regression analysis of the raw data. Chapter VI will present the final empirical models developed from the analysis summarized in this chapter.

Analysis of Empirical Data

This section contains the results of an analysis of software errors by type. Since error data by category type was not available for Project 3, only error data from Projects 1 and 2 were analyzed.

Using the error category list in Table 2, the question naturally arises "how many of each type were there?" This analysis took place only at the major category level, and only errors which required a change to the source code or data base were examined. Categories "DATA INPUT ERRORS" and "DATA OUTPUT ERRORS" were combined into "INPUT/OUTPUT ERRORS". Categories "DATA HANDLING ERRORS" and "ARRAY PROCESSING ERRORS" were combined into "DATA HANDLING ERRORS. Categories "OPERATION ERRORS", "DOCUMENTATION ERRORS" and "PROGRAM EXECUTION ERRORS" are included in category "OTHER".

Figure 10 shows a percentage breakdown by major category for Projects 1 and 2. It also shows a percentage breakdown when Projects 1 and 2 are combined. Percentage breakdowns appear to be reasonable for the type software for each project. Project 2 is an on-line system and Project 1 is a batch system. Variations exist in the percentage breakdowns because of the kinds of operations the programs are performing. Project 1 programs are performing mostly data
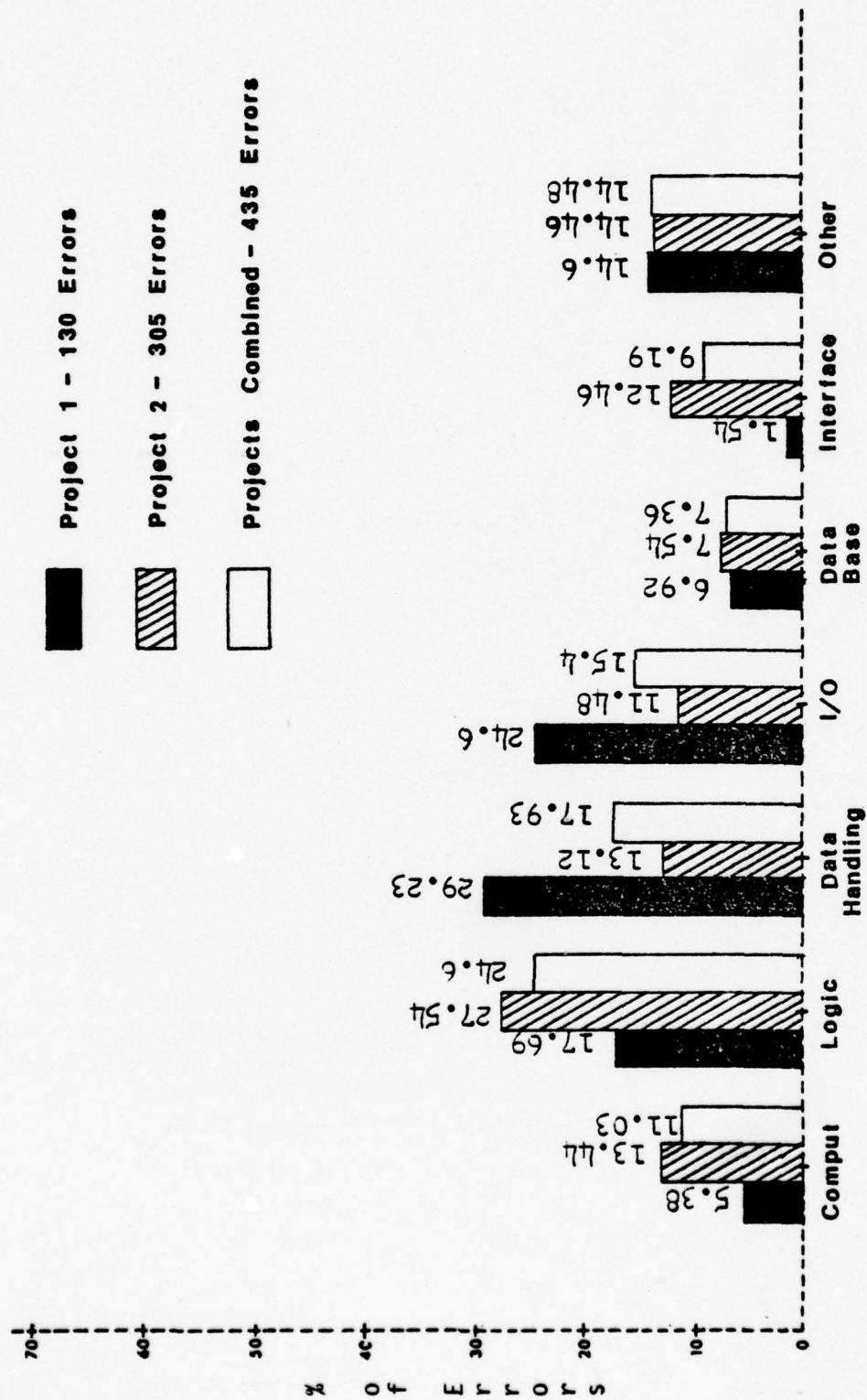
ERROR CATEGORIES

Figure 10. Percentage of Error Types for Projects 1 and 2

input/output and data transfers. The logic within the programs is not very complicated. On the other hand the programs in Project 2 are doing more computations on the data and the logic flow is more complicated.

The data for each project supports the notion that the distributions of the types are application dependent. However, when the data from the two projects are combined, the relative importance of the percentages changes. As one can see the logic type has the highest percentage (24.6% vs 17.9%). It is suggested that this will be true in the general case.

Summary of Regression Analysis

Regression Analysis Concepts

Situations exist where there are two or more variables that are functionally related. The problem is to understand this relationship. This is not an easy thing to do since the relationship may be a simple or a complex one. Most often, the functional relationship is extremely complex, or completely unknown. The goal is to obtain a better understanding of the relationship and then use that information for prediction, process optimization or control.

The technique usually employed in these investigations of relationships between variables is known as regression analysis. Regression analysis assumes the existence of a functional relationship

$$Y = F[x(1), x(2), \ldots, x(n); B(0), B(1), \ldots, B(n)] + e,$$

where Y is the response (or dependent) variable,
$x(i)$ $(i=1,2,...,n)$ are the independent variables, $B(j)$
$(j=0,1,...,n)$ are unknown parameters, and e is a random error component. The problem consists of estimating the
unknown parameters in the above equation.

The kind of relationship between Y and the independent variables determine the type of regression analysis to perform. If the assumption of linearity appears reasonable then linear regression analysis can be used. If linearity does not seem reasonable then some other analysis technique must be employed. Since this research assumes linearity, linear regression analysis techniques are used. The rest of this section briefly discusses linear regression analysis as related to this paper.

If one wishes to determine the relationship between a single independent variable, say x, and a single response or dependent variable, say Y, then use simple linear regression techniques. The equation to predict would be in the form

$$Y = B(0) + B(1)x + e,$$

where "$B(0)$" is the intercept, "$B(1)$" is the slope and "e" is the random error component. The procedure is to use the method of least squares to estimate "$B(0)$" and "$B(1)$" [68].

If one wishes to determine the relationship between many independent variables and a single dependent variable then use multiple linear regression techniques. The equation to predict would be in the form

$$Y = B(0) + B(1)x(1) + B(2)x(2) + ... + B(n)x(n) + e,$$

where B(i)'s are the unknown parameters (regression coeffi-
cients) to be estimated using the method of least squares .
Y is the dependent variable, and X(i)'s are the known inde-
pendent variables.

For our purpose, the independent variables are the
characteristic metrics (see Table 4). The equation would
be, if all metrics were included, similar to the following
equation

$N = B(0) + B(1)LC + B(2)IO + B(3)CO + B(4)DH + B(5)PC +$
$B(6)UBR + B(7)EXIT + B(8)STOP + B(9)OSC + B(10)CC + B(11)TS$
$+ B(12)NEX + B(13)NNEX + B(14)FD + B(15)RD + B(16)DD +$
$B(17)TD + B(18)DR + B(19)NCO + B(20)PAR + B(21)NL + B(22)RW,$
where B(i)'s are estimated using project data from Tables 5-7.

Most organizations do not want to expend the resources
to collect data. As the number of variables increase so
does the collection and maintenance costs for metric and er-
ror data. Therefore, it is desirable to have a minimum num-
ber of metric variables to collect and maintain. Thus, the
objectives of the regression analysis are to determine which
metric variables singly correlated with the number of errors
and to determine the "best" groups with the minimum number
of variables to predict the number of errors in a program.

The regression results presented in the following sec-
tions are summaries of outputs from the Statistical Analysis
System 76 [69]. For the interested reader reference [69]
explains different techniques for determining which vari-
ables of a collection of independent variables should most

likely be included in a regression model. Since all
techniques (forward, backward, stepwise, maximum r-square,
and minimum r-square) were available in SAS76, they were all
used initially to screen the independent variable list. Two
statistics, "r-square" and "F", are used to determine if a
linear relationship exists. "R-square" is the proportion of
variability in N that is explained by the relationship be-
tween N and the independent variables (characteristics met-
rics). "F" is a well known statistic used in tests of
hypothesis.

Simple Linear Regression Analysis Results

Each variable represents a metric which serves to meas-
ure to some degree the number of program errors. In order
to correlate the metric with the number of errors (N), a
single variable linear regression analysis was performed on
each metric variable.

A test of hypothesis was conducted on each metric to
determine if its regression on N was significant. All tests
were set up in the following manner with a .05 level of sig-
nificance

$$H(0): \quad B(1) = 0,$$

$$H(1): \quad B(1) \neq 0.$$

and under the assumption that the e(i)'s are normally dis-
tributed. The regression statistics for each respective
project is summarized in Tables 11-13. The "Decision"
column indicates if H(0) is rejected or accepted. Rejected

TABLE 11. SUMMARY OF SINGLE VARIABLE REGRESSION DATA

FOR PROJECT CNE

Metric Variable	R-square	F Value	Pr > F	Decision
LC	0.944435	50.99	0.0057	Reject H(0)
IO	0.212239	0.81	0.4349	Accept H(0)
CO	0.627788	5.06	0.1100	Accept H(0)
DH	0.943303	49.91	0.0058	Reject H(0)
PC	0.566996	3.93	0.1418	Accept H(0)
UBR	0.995852	720.16	0.0001	Reject H(0)
EXIT	0.285568	1.20	0.3535	Accept H(0)
STOP	0.056103	0.18	0.7013	Accept H(0)
OSC	0.074677	0.24	0.6564	Accept H(0)
CC	0.000000	0.00	1.0000	Accept H(0)
TS	0.677116	6.29	0.0871	Accept H(0)
NEX	0.945817	52.37	0.0054	Accept H(0)
NNEX	0.232533	0.91	0.4107	Accept H(0)
FD	0.111622	0.38	0.5827	Accept H(0)
RD	0.745010	8.77	0.0595	Accept H(0)
DD	0.430402	2.27	0.2292	Accept H(0)
TD	0.470261	2.66	0.2012	Accept H(0)
DR	0.885232	23.14	0.0171	Reject H(0)
NCO	0.095886	0.32	0.6121	Accept H(0)
PAR	0.421938	2.19	0.2355	Accept H(0)
NL	0.557331	3.78	0.1472	Accept H(0)
RW	0.877502	21.49	0.0189	Reject H(0)

TABLE 12. SUMMARY OF SINGLE VARIABLE REGRESSION DATA

FOR PROJECT TWO

Metric Variable	R-square	F Value	Pr > F	Decision
LC	0.952913	242.85	0.0001	Reject H(0)
IO	0.769078	39.97	0.0001	Reject H(0)
CO	0.413572	8.46	0.0131	Reject H(0)
DH	0.585479	16.95	0.0014	Reject H(0)
PC	0.683309	25.89	0.0003	Reject H(0)
UBR	0.684094	25.99	0.0003	Reject H(0)
EXIT	0.521244	13.06	0.0035	Reject H(0)
STOP	0.281546	4.70	0.0509	Accept H(0)
OSC	0.000000	0.00	1.0000	Accept H(0)
CC	0.237354	3.73	0.0772	Accept H(0)
TS	0.579287	16.52	0.0016	Reject H(0)
NEX	0.869163	79.72	0.0001	Reject H(0)
NNEX	0.256202	4.13	0.0648	Accept H(0)
FD	0.001341	0.02	0.9011	Accept H(0)
RD	0.124145	1.70	0.2166	Accept H(0)
DD	0.267050	4.37	0.0585	Accept H(0)
TD	0.256989	4.15	0.0643	Accept H(0)
DR	0.884833	92.20	0.0001	Reject H(0)
PAR	0.807197	50.24	0.0001	Reject H(0)
NL	0.715260	30.14	0.0001	Reject H(0)
RW	0.594347	17.58	0.0012	Reject H(0)
NCO	0.709362	29.29	0.0002	Reject H(0)

TABLE 13.   SUMMARY OF SINGLE VARIABLE REGRESSION DATA

FOR PROJECT THREE

Metric Variable	R-square	F Value	Pr > F	Decision
LC	0.830952	216.28	0.0001	Reject H(0)
IO	0.081709	3.92	0.0541	Accept H(0)
CO	0.696377	100.92	0.0001	Reject H(0)
DH	0.751509	133.07	0.0001	Reject H(0)
PC	0.295987	18.50	0.0001	Reject H(0)
UBR	0.821589	202.62	0.0001	Reject H(0)
EXIT	0.209254	11.64	0.0014	Reject H(0)
STOP	0.014800	0.66	0.4206	Accept H(0)
OSC	0.174450	9.30	0.0039	Reject H(0)
CC	0.001323	0.06	0.8103	Accept H(0)
TS	0.755609	136.04	0.0001	Reject H(0)
NEX	0.809248	186.67	0.0001	Reject H(0)
NNEX	0.271785	16.42	0.0002	Reject H(0)
FD	0.010272	0.46	0.5027	Accept H(0)
RD	0.162182	8.52	0.0055	Accept H(0)
DD	0.291375	18.14	0.0001	Reject H(0)
TD	0.286922	17.70	0.0001	Reject H(0)
DR	0.799424	175.37	0.0001	Reject H(0)
NCO	0.023480	1.06	0.3093	Accept H(0)
PAR	0.647323	80.76	0.0001	Reject H(0)
NL	0.668134	88.58	0.0001	Reject H(0)
RW	0.742020	126.56	0.0001	Reject H(0)

means that the regression of the metric on N is signifi-
cant. Accepted means that the regression is not signifi-
cant.

A summary of the significance of the regression of
single metrics on N is presented in Table 14. An "*" means
the regression is significant. It is significant that "LC"
is the highest(regardless of software type, operating mode
or other project differences) in Projects 2 and 3 and second
in Project 1. Variables "DH" and "RW" were also significant
for all projects.

Although most variables turned out to be significant
for one or the other projects, "LC" and "UBR" are more im-
portant since these can be obtained before coding starts
(they can be read directly from "control flow charts). The
predicted linear equations for all variables by project is
contained in Table 15. An "*" means no equation was pre-
dicted for this project.

Multiple Linear Regression Analysis Results

The purpose of the multiple regression analysis was to
determine which metric variables should most likely be in-
cluded in a regression model. Mainly we were interested in
screening the list of 22 metric variables shown in Table 4
to eliminate the ones that did not influence software error
data.

TABLE 14.   SUMMARY OF SIGNIFICANCE OF REGRESSION
FOR ALL PROJECTS

Metric Variable	Project		
	One	Two	Three
LC	*	*	*
DH	*	*	*
UBR	*	*	*
DR	*	*	*
RW	*	*	*
CO		*	*
PC		*	*
EXIT		*	*
NEX		*	*
TS		*	*
PAR		*	*
NL		*	*
NCO		*	
OSC			*
NNEX			*
DD			*
TD			*
IO			
STOP			
CC			
FD			
RD			

TABLE 15. SINGLE VARIABLE MODELS FOR PREDICTING

THE NUMBER OF ERRORS IN COBOL PROGRAMS

Metric Variable	Project One		Project Two		Project Three	
	Inter-cept	Slope	Inter-cept	Slope	Inter-cept	Slope
LC	2.902	0.587	3.7311	0.319	4.355	0.038
IO	*	*	5.848	0.303	*	*
CO	*	*	9.319	0.362	3.157	0.228
DH	4.623	0.404	5.640	0.104	1.525	0.040
PC	*	*	8.567	0.371	8.758	0.041
UBR	-1.683	1.047	12.621	0.122	4.110	0.060
EXIT	*	*	9.222	0.714	7.753	0.399
STOP	*	*	*	*	6.492	0.234
CC	*	*	*	*	*	*
TS	*	*	2.645	0.022	0.632	0.010
NEX	*	*	- 0.422	0.056	2.272	0.012
NNEX	*	*	*	*	3.579	0.020
FD	*	*	*	*	*	*
RD	*	*	*	*	*	*
DD	*	*	*	*	3.3839	0.024
TD	*	*	*	*	3.625	0.022
DR	-1.153	0.064	- 0.973	0.010	2.325	0.005
NCO	*	*	- 0.153	0.088	*	*
PAR	*	*	7.294	0.334	2.871	0.106
NL	*	*	- 0.326	0.017	- 0.477	0.010
RW	2.661	0.139	6.015	0.043	1.127	0.014

Analysis Using all Metric Variables

The basic approach to this part of the analysis was to
study the outputs from all five techniques referenced above
and select the sets of variables most frequently included
for each project. Table 16 lists a few of the sets of vari-
ables selected for all projects. The highest "r-square"
value is given when the same set was selected more than
once. Column "Decision" reflects the decision relative to
the hypothesis

$$H(0): \quad B(1)=B(2)...=B(n) = 0,$$

against

$$H(1): \quad B(i) \neq 0 \text{ for at least one } i.$$

and under the assumption that the e(i)'s are normally dis-
tributed. At a .05 significance level, at least one B(i) is
significantly different from zero for all selected groups.
Table 17 contains the final list of variables chosen from
those shown in Table 16. Table 18 contains a summary of the
predicted equations for each set of variables by project.

The preceding discussion was based upon an objective
analysis of 22 variables without considering their relation-
ship to each other. Since some of the 22 variables were
known to be functionally related, i.e.,
TS = NEX + NNEX and TD = FD + RD + DD, a subset of variables
considered unrelated was selected and used in a regression
analysis. These variables are LC, IO, CO, DH, PC, UBR,
EXIT, STOP, OSC, CC, TD, PAR, and DR. The results from this
analysis is presented in the next section.

TABLE 16. VARIABLES SELECTED FOR MODELS

No in Group	Variables Selected	R Square	F Value	Pr>F	Decision
2	LC UBR	0.9585	127.11	0.0001	R H(0)
	LC STOP	0.9911	612.28	0.0001	R H(0)
	UBR EXIT	0.9988	855.77	0.0012	R H(0)
3	UBR EXIT NNEX	0.9999	999.99	0.0001	R H(0)
	LC UBR CC	0.9935	850.60	0.0001	R H(0)
	LC CO STOP	0.9999	611.51	0.0001	R H(0)
	LC CC NEX	0.9946	506.40	0.0001	R H(0)
4	UBR IO EXIT NNEX	1.0000	999.99	0.0001	R H(0)
	DD TD DR RW	1.0000	999.99	0.0001	R H(0)
	LC CO UBR STOP	0.9915	461.51	0.0001	R H(0)
	LC EXIT CC NEX	0.9949	441.86	0.0001	R H(0)
	LC UBR OSC CC	0.8660	66.20	0.0001	R H(0)
	PC STOP CC NEX	0.8784	74.07	0.0001	R H(0)
5	UBR EXIT NNEX TS RW	1.0000	649.70	0.0001	R H(0)
	LC CO UBR STOP DR	0.9955	354.02	0.0001	R H(0)
	LC CO UBR DR PAR	0.9955	354.02	0.0001	R H(0)
	LC PC EXIT STOP NEX	0.9975	652.77	0.0001	R H(0)
	LC UBR OSC CC FD	0.8716	54.29	0.0001	R H(0)
	PC STOP CC NNEX NL	0.8808	59.08	0.0001	R H(0)
10	LC IO CO UBR EXIT STOP DD TD DR PAR	0.9995	643.00	0.0001	R H(0)
	LC IO CO DH PC UBR DD TD DR PAR	0.9951	645.00	0.0001	R H(0)
	LC IO CO UBR CC FD DR NL PAR RW	0.9927	411.44	0.0002	R H(0)
	LC PC STOP NEX FD RD DD DR TS RW	0.9999	2310.7	0.0001	R H(0)
	LC IO CO UBR STOP OSC CC FD RD TD	0.8662	27.25	0.0001	R H(0)

TABLE 16.   VARIABLES SELECTED FOR MODELS--Continued

No in Group	Variables Selected	R Square	F Value	Pr>F	Deci-sion
10	LC PC CC NEX NNEX RD DD TD NL TS	0.9135	36.95	0.0001	R H(0)
	LC IO CO DH PC UBR EXIT OSC CC TD	0.9955	408.15	0.0001	R H(0)
	LC IO CO UBR STOP OSC CC NEX FD DR	0.8833	27.84	0.0001	R H(0)
	DH PC STOP CC NEX NNEX FD RD TS NL	0.8908	28.55	0.0001	R H(0)
15	LC IO CO UBR EXIT CC FD RD STOP TD DR NL PAR RW DD	1.0000	99999.	0.0001	R H(0)
	LC IO DH PC UBR CC NEX RD NNEX DD TD DR NCO TS NL	0.9216	23.49	0.0001	R H(0)
	LC CO DH PC UBR OSC CC FD RD DD TD NCO NL TS DR	0.9186	22.56	0.0001	R H(0)
20	LC IO CO DH PC UBR STOP CC OSC TS NEX NNEX FD RD DD TD DR NCO NL PAR	0.9244	15.28	0.0001	R H(0)
	LC IO CO DH PC UBR EXIT CC STOP OSC TS NEX NNEX FD RD DD TD DR NL PAR	0.9244	13.98	0.0001	R H(0)

TABLE 17.   FINAL LISTS OF METRIC VARIABLES SELECTED

Metric Variable	Number of Variables in models				
	2	5	10	15	20
LC	*	*	*	*	*
UBR	*	*	*	*	*
IO		*	*	*	*
DH		*	*	*	*
EXIT		*	*	*	*
CO			*	*	*
PC			*	*	*
OSC			*	*	*
CC			*	*	*
STOP				*	*
TD			*	*	*
DR				*	*
PAR				*	*
NL				*	*
RW				*	*
TS					*
NNEX					*
FD					*
DD					*
NCO					*
NEX					
RD					

TABLE 18. MULTIPLE VARIABLE MODELS FOR PREDICTING THE NUMBER

OF ERRORS IN COBOL PROGRAMS

PROJECT NO.	MODELS *
1	$\hat{N} = -1.556 + 0.029LC + 0.998UBR$
2	$\hat{N} = 3.971 + 0.302LC + 0.009UBR$
	$\hat{N} = -1.506 + 0.256LC + 0.124I\emptyset - 0.003DH + 0.003UBR - 0.130EXIT$
3	$\hat{N} = 4.072 + 0.022LC + 0.027UBR$
	$\hat{N} = 3.327 + 0.018LC + 0.006I\emptyset + 0.007DH + 0.0246UBR - 0.048EXIT$
	$\hat{N} = 5.633 + 0.020LC + 0.019I\emptyset - 0.015C\emptyset + 0.012DH - 0.009PC + 0.022UBR - 0.029EXIT + 0.049\emptyset SC - 2.392CC - 0.001TD$
	$\hat{N} = 7.062 + 0.014LC + 0.032I\emptyset + 0.002C\emptyset + 0.015DH + 0.001PC + 0.034UBR - 0.012EXIT - 1.927ST\emptyset P + 0.055\emptyset SC - 2.087CC + 0.003TD + 001DR - 0.029PAR - 0.002NL - 0.001RW$
	$\hat{N} = 5.922 - 0.323LC - 0.302I\emptyset - 0.312C\emptyset - 0.299DH - 0.342PC - 0.275UBR - 0.047EXIT - 1.449ST\emptyset P - 0.271\emptyset SC - 2.589CC + 0.324TS - 0.336NNEX + 0.065FD - 0.078DD + 0.094TD + 0.002DR + 0.012NC\emptyset - 0.044PAR - 0 - 011NL + 0.001RW$

*0's are slashed to distinguish from zeros.

Analysis of Reduced Sets of Unrelated Variables

It is appropriate at this time to point out that analysis was not performed for a project containing a number of observations less than the number of metric variables.

All tests of hypothesis were set up in the following manner with a 0.05 level of significance

$$H(0): \quad B(1)=B(2)=...=B(n)=0$$

against

$$H(1): \quad B(i) \neq 0, \text{ for at least one } i,$$

and under the assumption that the $e(i)$'s are normally distributed. The results of this analysis are summarized in Table 19. The regression is significant. Therefore, this final set of 13 metrics is a good predictor of software errors.

Conclusions

The main purpose of the preceding analysis was to determine if program characteristics metrics, which measure program complexity, are predictors of the number of errors in COBOL programs. It was shown, through simple linear and multiple linear regression analysis, that the number of errors in a COBOL program is a function of its structure which is measured by characteristics metrics.

A set of 13 unrelated metrics was chosen as the final group of metrics to predict the number of software errors. The next chapter will specifically discuss how this set is used as a measure of program complexity.

TABLE 19. SUMMARY OF REGRESSION ANALYSIS OF REDUCED SET OF VARIABLES

PROJECT	MODELS *	R SQUARE	F VALUE	PR > F	DECISION
1	$\hat{N}$ = 1.180 + 1.088UBR - 0.460EXIT	0.9988	855.77	0.0012	R H (0)
2	$\hat{N}$ = 1.92 + 0.191LC + 0.103CO + 0.112UBR - 0.260PAR + 0.003DR	0.9968	510.88	0.0001	R H (0)
	$\hat{N}$ = - 3.836 + 0.231LC + 0.031CO + 0.031DH + 0.103PC + 0.042UBR - 0.202EXIT + 6.133STOP - 0.011TD - 0.229PAR + 0.004DR	0.9993	451.06	0.0002	R H (0)
3	$\hat{N}$ = 4.072 + 0.022LC + 0.027UBR	0.8463	118.40	0.0001	R H (0)
	$\hat{N}$ = 5.583 + 0.021LC + 0.0171D + 0.026UBR + 0.050SC - 2.025CC	0.8702	53.61	0.0001	R H (0)
	$\hat{N}$ = 7.188 + 0.010LC + 0.0261D + 0.010DH + 0.030UBR - 0.019EXIT - 2.105STOP + 0.051SC - 2.146CC - 0.037PAR + 0.001DR	0.8844	26.77	0.0001	R H (0)
	$\hat{N}$ = 7.215 + 0.010LC + 0.0271D + 0.008CO + 0.110DH + 0.002PC + 0.032UBR - 0.015EXIT - 2.104STOP + 0.052SC - 2.143CC - 0.0002TD - 0.043PAR + 0.001DR	0.8845	18.84	0.0001	R H (0)

*0's are slashed to distinguish them from zeros.

VI. A MEASURE OF PROGRAM COMPLEXITY

Introduction

Initially it was hypothesized that the number of soft-
ware errors could be predicted from the internal complexity
of the programs. But what does one mean by "internal com-
plexity"? Is it a property that can be observed and meas-
ured, and perhaps even related to the number of errors in
programs?

Complexity of any object is some measure of the mental
effort [4,17] required to understand that object. In gener-
al usage, the complexity of an object is a function of the
relationships among the components of the object. As ap-
plied to computer programs, it is a measure of the internal
structural characteristics of the program. The previous
chapter presented the results of an analysis that showed
that actual program characteristics were related to the num-
ber of program errors. The purpose of this chapter is to
define a "program complexity measure" from these basic char-
acteristics.

Measures of Program Complexity

A program is made up of many components such as object
instructions, data base descriptions, external data bases,

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other external programs such as the operating system and
other application programs, program logic, etc. These com-
ponents and the relationships among them determine program
complexity. The problem is to measure the degree to which
certain relationships exist within a program. For example,
the number of input/output statements measures, in some
degree, whether an input/output relation exists between the
program and a data base. Complexity when applied to a spe-
cific relation is called local complexity. The complexity
of a program as a whole is defined in terms of local com-
plexities. There are 7 local complexities: control flow
complexity, input/output complexity, data use complexity,
computational complexity, data transfer complexity, struc-
ture design complexity, and interface complexity.

Control flow complexity is defined as the number of
logical relationships present in the source code. In a
COBOL program, these relations are manifested as IF, GOTO,
STOP, and PERFORM...UNTIL statements, and AND and OR condi-
tions. The Control Flow Complexity metric, CFC, can be
numerically evaluated for each program by calculation:

$$CFC = LC + UBR + STOP$$

A Normalized Control Flow metric, NCFC, is defined as NCFC =
CFC/1000.

Input/output complexity is defined as the number of I/O
statements. The Input/Output Complexity metric, abbreviated
as IOC, is

$$IOC = IO.$$

Data use complexity is defined as the ratio of data references (actual references to data items) to total data definitions. Many data reference errors are made because the assumptions made when defining data differs from the assumptions made when using the data. For example, when defining a data item as ALPHABETIC, it is assumed that only alphabetic data will be stored; but, when numeric data is stored in the data item it is assumed that the data item is declared "numeric" or "alphanumeric". As the number of data references increases relative to total definitions, the data use complexity increases. The Data Use Complexity metric, abbreviated as DUC, is calculated as

$$DUC = DR/TD.$$

Computational complexity is defined as the number of arithmetic statements such as ADD, MULTIPLY, COMPUTE, etc. The metric for this complexity is abbreviated as COC where

$$COC = CO.$$

Data transfer complexity is measured by the number of data transfer statements. This complexity metric, abbreviated as DHC, is evaluated by counting the number of data transfer statements (DHC = DH).

Interface complexity is measured by the number of system interfaces (number of system routines called) and the number of application routine interfaces (number of internal and external application routines called). The Interface Complexity metric, abbreviated as IC, is defined as follows:

$$IC = OSC + CC + PC,$$

where

OSC = number of system program interfaces

CC = number of compiler calls such as COPY

PC = number of application (internal and external) routine interfaces.

Structural design complexity is a measure of the number of distinct routines (number of components) in a program. The Structural Design Complexity metric referred to as SC, is numerically evaluated for each program by calculating:

$$SC = (PAR - EXIT) + 1.$$

The 1 accounts for the main control flow routine.

Total complexity is a function of the 7 local complexities discussed above. The Total Complexity metric, referred to as TC, is defined as follows:

$$TC = CPC + IOC + DUC + COC + DHC + IC + SC.$$

A Normalized Total Complexity metric, referred to as NTC, is defined as TC = TC/1000.

Regression Analysis of Complexity Metrics

Heretofore, data from 3 projects were used. But here, the complexity metrics are analyzed using the original 3 data bases plus 1 data base consisting of all 3 projects' data combined. The purpose for mixing the sources of data is to observe what happens when different types of programs, developed by different organizations, are mixed. Hereafter, the combined data base is referred to as Project 4. There are 65 observations (programs) in this data base. Tables

20-23 summarize the regression statistics for each respective project. The "Decision" column reflects the decision at the .05 significance level relative to the hypothesis

$$H(0): \quad B = 0,$$

against

$$H(1): \quad B \neq 0,$$

and under the assumption that the e(i)'s are normally distributed. Table 24 presents a summary of the regression significance, at the .05 level, of the complexity metrics by project.

The "best" complexity models, predicted by the Maximum R-square technique, are listed by project in Table 25. The models for total complexity and the normalized metrics, TC, NTC and NCFC, are listed in Table 26. Actual data points (plotted as '+') and the regression line for project 3 are shown in Figures 11-20.

Conclusions

The purpose of this chapter was to define and develop a "program complexity measure" from 13 unrelated characteristics metrics selected from the analysis presented in the previous chapter. Seven local complexities were defined and used to develop a measure of total program complexity. Metrics for each complexity were defined also. It was shown, through simple linear and multiple linear regression analysis, that the number of errors in COBOL programs is a function of these complexity metrics.

Linear models developed from these metrics can be used to predict the number of errors in COBOL programs. The "best" single variable model for predicting errors is the Control Flow Complexity metric model. The "best" multiple variable model for predicting errors is the one that contains all 7 local complexity metrics. Analysis of Project 4 showed that the latter model can be used when dealing with many types of programs that are developed by different organizations. However, it is suggested that each organization estimate the model parameters relative to error data from its development projects.

TABLE 20.   SUMMARY OF THE COMPLEXITY METRICS REGRESSION

DATA FOR PROJECT 1

Complexity Metric Variable	R-square	F Value	Pr > F	Decision
CFC	0.975512	119.51	0.0016	Reject H(0)
IOC	0.212239	0.81	0.4349	Accept H(0)
DUC	0.258828	1.05	0.3814	Accept H(0)
COC	0.627788	5.06	0.1100	Accept H(0)
DHC	0.943303	49.91	0.0058	Reject H(0)
IC	0.091318	0.30	0.6212	Accept H(0)
SC	0.459725	2.55	0.2084	Accept H(0)
TC	0.934449	42.77	0.0073	Reject H(0)
NTC	0.934449	42.77	0.0073	Reject H(0)
NCFC	0.975512	119.51	0.0016	Reject H(0)

TABLE 21. SUMMARY OF THE COMPLEXITY METRICS REGRESSION

DATA FOR PROJECT 2

Complexity Metric Variable	R-square	F Value	Pr > F	Decision
CFC	0.824537	56.39	0.0001	Reject H(0)
IOC	0.769078	39.97	0.0001	Reject H(0)
DUC	0.061079	0.78	0.3943	Accept H(0)
COC	0.413575	8.46	0.0131	Reject H(0)
DHC	0.585479	16.95	0.0014	Reject H(0)
IC	0.727358	32.01	0.0001	Reject H(0)
SC	0.660955	23.39	0.0004	Reject H(0)
TC	0.903222	112.00	0.0001	Reject H(0)
NTC	0.903222	112.00	0.0001	Reject H(0)
NCFC	0.824537	56.39	0.0001	Reject H(0)

TABLE 22. SUMMARY OF THE COMPLEXITY METRICS REGRESSION

DATA FOR PROJECT 3

Complexity Metric Variable	R-square	F Value	Pr > F	Decision
CFC	0.845919	241.56	0.0001	Reject H(0)
IOC	0.081709	3.92	0.0541	Accept H(0)
DUC	0.385898	27.65	0.0001	Reject H(0)
COC	0.696377	100.92	0.0001	Reject H(0)
DHC	0.751509	133.07	0.0001	Reject H(0)
IC	0.341395	22.81	0.0001	Reject H(0)
SC	0.686814	96.49	0.0001	Reject H(0)
TC	0.806581	183.48	0.0001	Reject H(0)
NTC	0.806581	183.48	0.0001	Reject H(0)
NCFC	0.845919	241.56	0.0001	Reject H(0)

TABLE 23. SUMMARY OF THE COMPLEXITY METRICS REGRESSION
DATA FOR PROJECT 4

Complexity Metric Variable	R-square	F Value	Pr > F	Decision
CPC	0.300097	27.01	0.0001	Reject H(0)
IOC	0.172233	13.11	C.C006	Reject H(0)
DUC	0.151020	11.21	0.0014	Reject H(0)
COC	0.346999	33.48	C.0001	Reject H(0)
DHC	0.270823	23.40	0.0001	Reject H(0)
IC	0.106096	7.48	0.0081	Reject H(0)
SC	0.206157	16.36	C.0001	Reject H(0)
TC	0.304956	27.64	C.0001	Reject H(0)
NTC	0.304956	27.64	0.0001	Reject H(0)
NCPC	0.300097	27.01	0.0001	Reject H(0)

TABLE 24. REGRESSION SIGNIFICANCE OF COMPLEXITY METRICS

VERSUS NUMBER OF ERRORS

Complexity Metric Variable	Project			
	1	2	3	4
CFC	*	*	*	*
DEC	*	*	*	*
TC	*	*	*	*
NTC	*	*	*	*
NCFC	*	*	*	*
COC		*	*	*
IC		*	*	*
SC		*	*	*
IOC		*		*
DUC			*	*

TABLE 25. COMPLEXITY MODELS FOR PREDICTING THE NUMBER OF

ERRORS IN COBOL PROGRAMS

PROJECT	MODELS *	R-SQUARE
1	$\hat{N}$ = 0.207 + 0.382CFC	0.97551
	$\hat{N}$ = 0.205 + 0.326CFC + 0.250COC	0.99775
	$\hat{N}$ = 3.207 + 0.326CFC + 0.279COC - 0.163IC	0.99999
	$\hat{N}$ = 3.156 + 0.326CFC - 0.017IOC + 0.283COC - 0.146IC	1.0000
2	$\hat{N}$ = 8.943 + 0.096CFC	0.82456
	$\hat{N}$ = 2.015 + 0.083CFC + 0.233COC	0.98091
	$\hat{N}$ = 0.845 + 0.074CFC + 0.225COC + 0.017OIC	0.98787
	$\hat{N}$ = -0.903 + 0.071CFC + 0.263DUC + 0.225COC + 0.020DHC	0.98978
	$\hat{N}$ = 0.098 + 0.097CFC + 0.270DUC + 0.216COC + 0.062IC - 0.133SC	0.99130
	$\hat{N}$ = -1.014 + 0.086CFC + 0.021IOC + 0.302DUC + 0.206COC + 0.062IC - 0.103SC	0.99193
	$\hat{N}$ = -1.291 + 0.079CFC + 0.019IOC + 0.314DUC + 0.208COC + 0.005DHC + 0.056IC - 0.074SC	0.59199

*O's are slashed to distinguish them from zeros.

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TABLE 25--continued

PROJECT	MODELS *	R-SQUARE
3	$\hat{N}$ = 4.069 + 0.024CFC	0.84591
	$\hat{N}$ = 3.531 + 0.021CFC + 0.006DIIC	0.84804
	$\hat{N}$ = 3.451 + 0.021CFC + 0.0080DIIC - 0.004IC - 0.004IC	0.84937
	$\hat{N}$ = 3.253 + 0.021CFC + 0.004IDC + 0.007DIHC - 0.004IC	0.84965
	$\hat{N}$ = 3.244 + 0.022CFC + 0.006IDC - 0.017COC + 0.009DIIC - 0.005IC	0.85012
	$\hat{N}$ = 3.102 + 0.022CFC + 0.006IDC + 0.045DUC - 0.018COC + 0.009DIHC - 0.006IC	0.85020
	$\hat{N}$ = 3.094 + 0.022CFC + 0.008IDC + 0.044DUC - 0.017COC + 0.009DIHC - 0.005IC - 0.005SC	0.85025
4	$\hat{N}$ = 6.789 + 0.254CDC	0.34700
	$\hat{N}$ = 3.890 + 0.0611DC + 0.210CDC	0.37532
	$\hat{N}$ = 3.784 + 0.011CFC + 0.066IDC + 0.131CDC	0.39897
	$\hat{N}$ = 4.509 + 0.025CFC + 0.082IDC + 0.109CDC - 0.079SC	0.41620
	$\hat{N}$ = 4.433 + 0.028CFC + 0.091IDC + 0.119CDC + 0.027IC - 0.139SC	0.42830
	$\hat{N}$ = 2.403 + 0.026CFC + 0.088IDC + 0.527DUC + 0.115CDC + 0.024IC - 0.136SC	0.43592
	$\hat{N}$ = 2.845 + 0.029CFC + 0.093IDC + 0.495DUC + 0.119CDC - 0.007DIHC + 0.020IC - 0.138SC	0.43695

TABLE 26.   TOTAL AND NORMALIZED COMPLEXITY MODELS BY PROJECT

PROJECT	MODELS
1	$\hat{N} = -3.728 + 0.153TC$
	$\hat{N} = -3.728 + 153.060NTC$
	$\hat{N} = 0.287 + 381.860NCFC$
2	$\hat{N} = 1.374 + 0.042TC$
	$\hat{N} = 1.374 + 41.977NTC$
	$\hat{N} = 8.943 + 95.763NCFC$
3	$\hat{N} = 2.220 + 0.011TC$
	$\hat{N} = 2.220 + 11.222NTC$
	$\hat{N} = 4.069 + 23.830NCFC$
4	$\hat{N} = 7.489 + 0.012TC$
	$\hat{N} = 7.489 + 11.666NTC$
	$\hat{N} = 9.521 + 24.370NCFC$
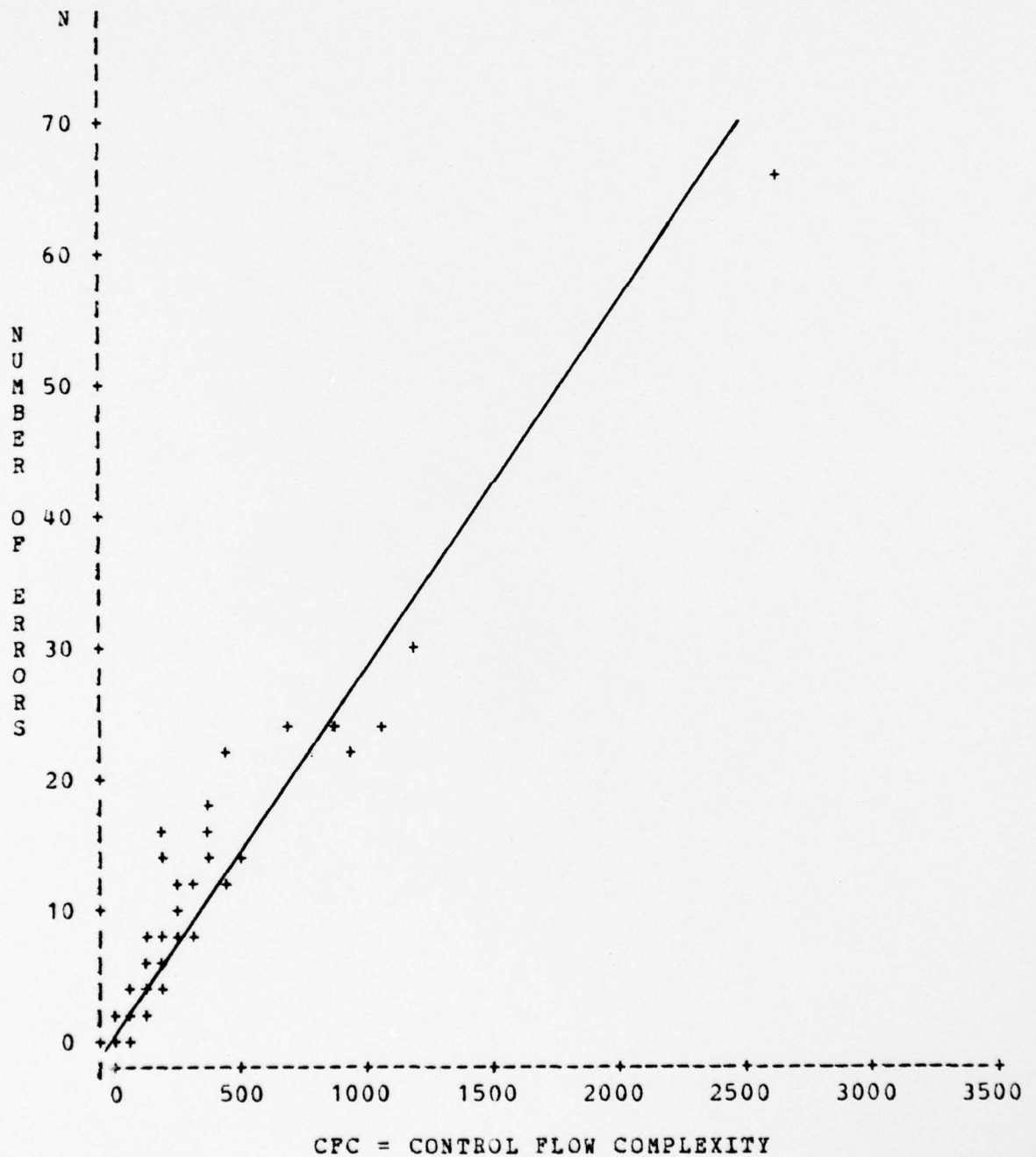
Figure 11. Plot of Control Flow Complexity Model for Project 3
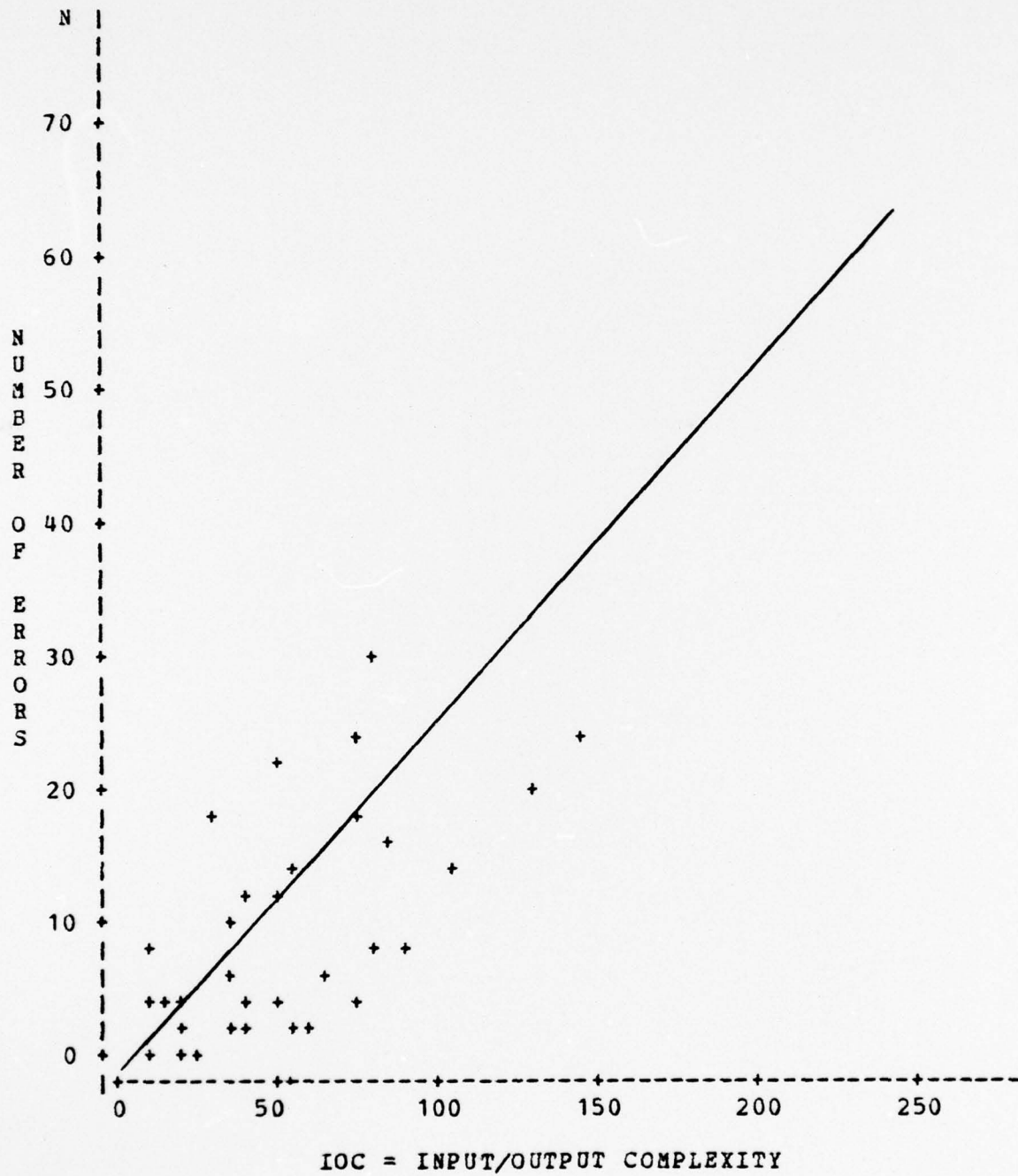
Figure 12.   Plot of I/O Complexity Model for Project 3
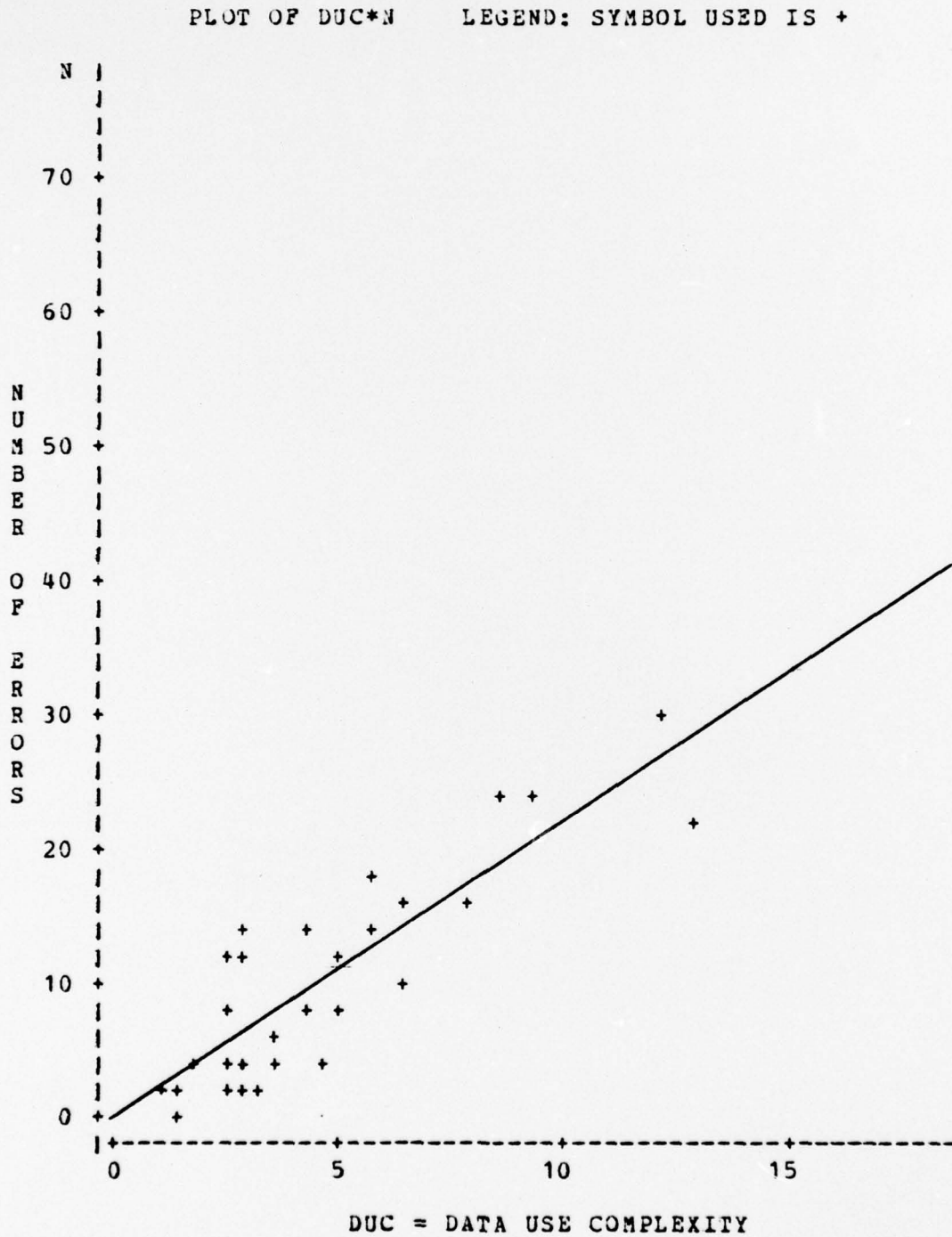
Figure 13. Plot of the Data Use Complexity Model for Project 3

PLOT OF COC*N   LEGEND: SYMBOL USED IS +
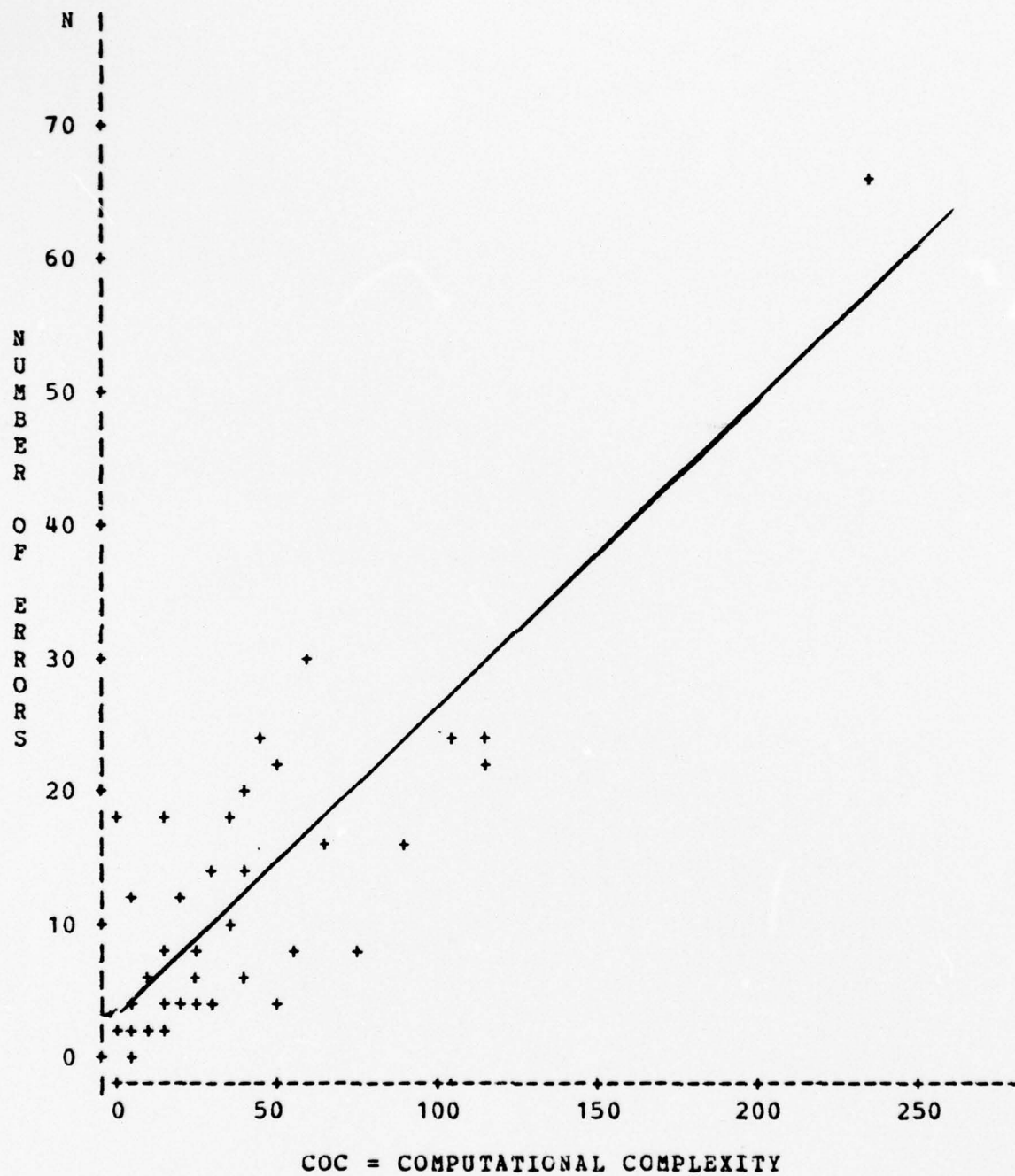
Figure 14. Plot of the Computational Complexity Model for Project 3

PLOT OF DHC*N   LEGEND: SYMBOL USED IS +

DHC = DATA HANDLING COMPLEXITY
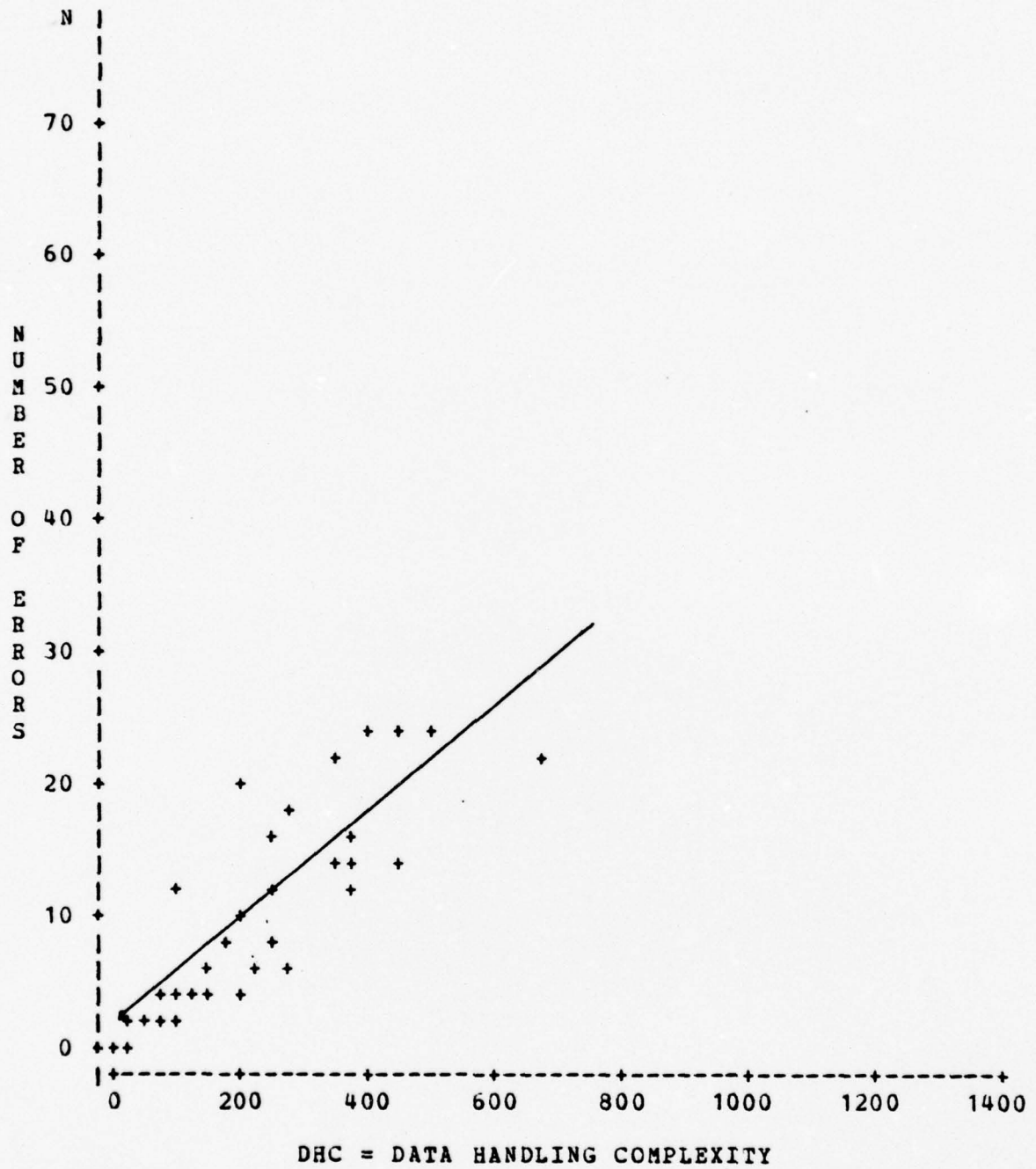
Figure 15.   Plot of the Data Handling Complexity Model for Project 3

PLOT OF IC*N   LEGEND: SYMBOL USED IS +

IC = INTERFACE COMPLEXITY
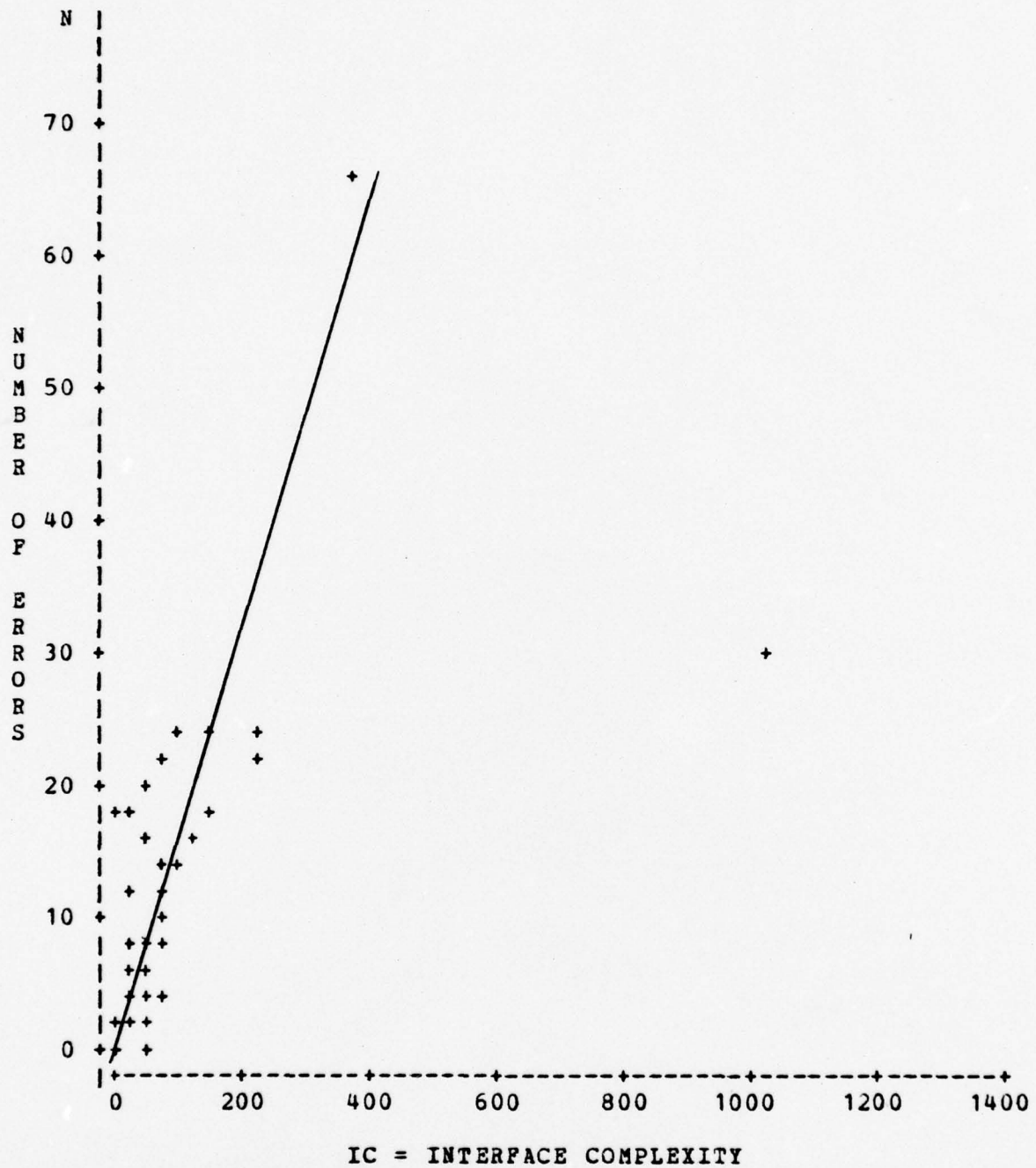
Figure 16. Plot of the Interface Complexity Model for Project 3

PLOT OF SC*N   LEGEND: SYMBOL USED IS +

SC = STRUCTURE DESIGN COMPLEXITY
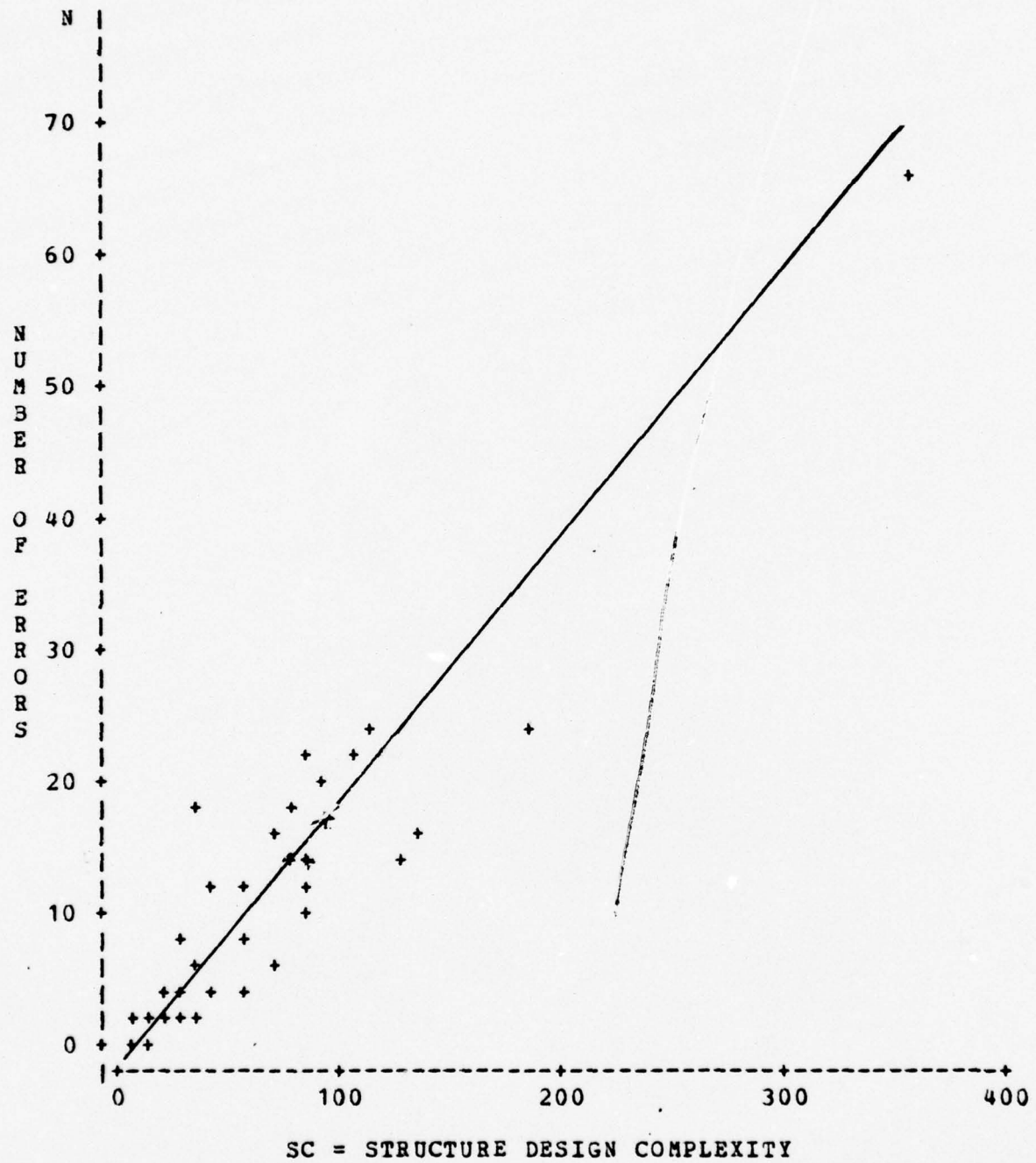
Figure 17. Plot of the Structure Design Complexity Model for Project 3

PLOT OF TC*N   LEGEND: SYMBOL USED IS +
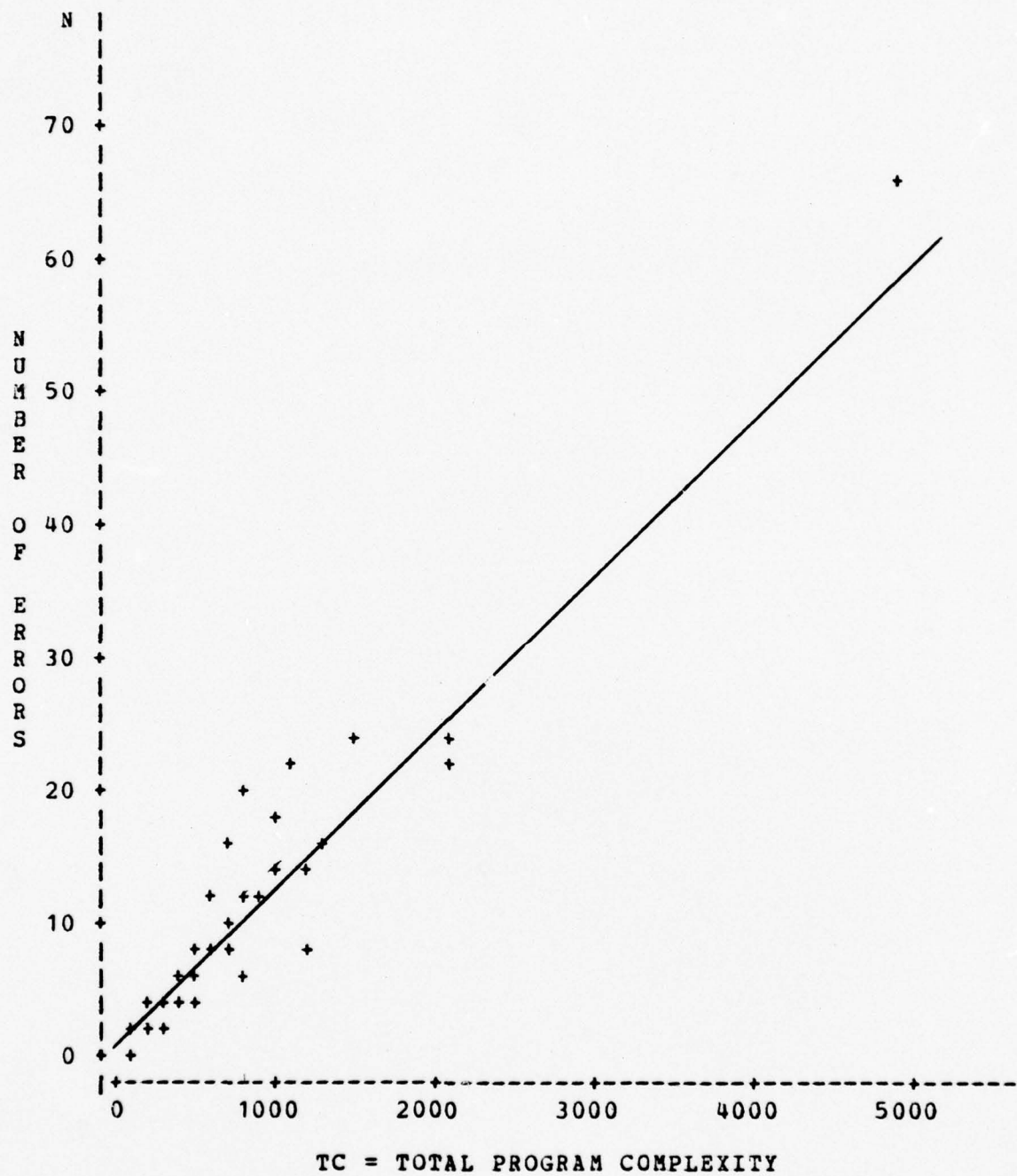
Figure 18. Plot of the Total Program Complexity Model for Project 3

PLOT OF NTC*N   LEGEND: SYMBOL USED IS +

NTC = NORMALIZED TOTAL COMPLEXITY
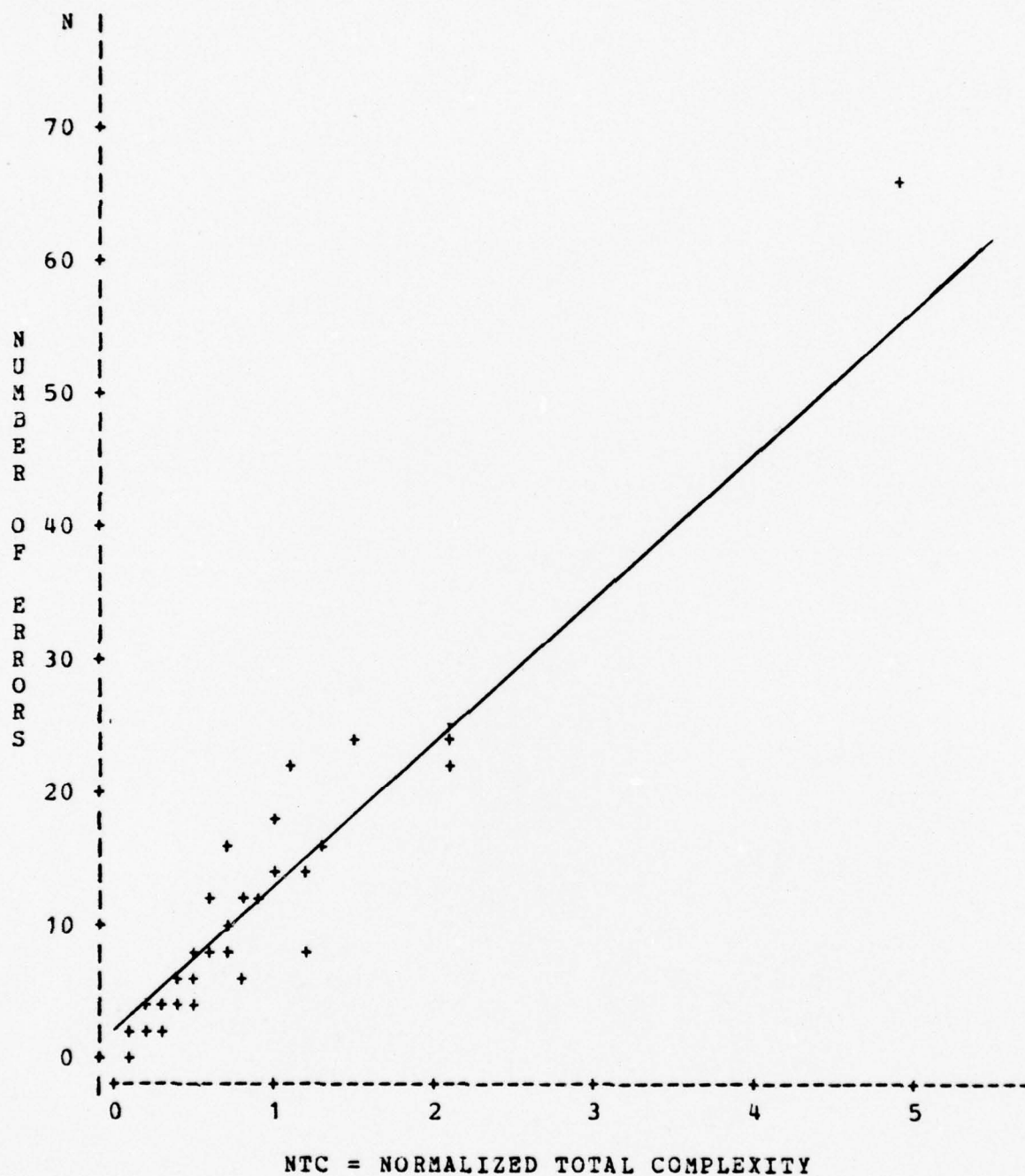
Figure 19.   Plot of the Normalized Total Complexity Model for Project 3
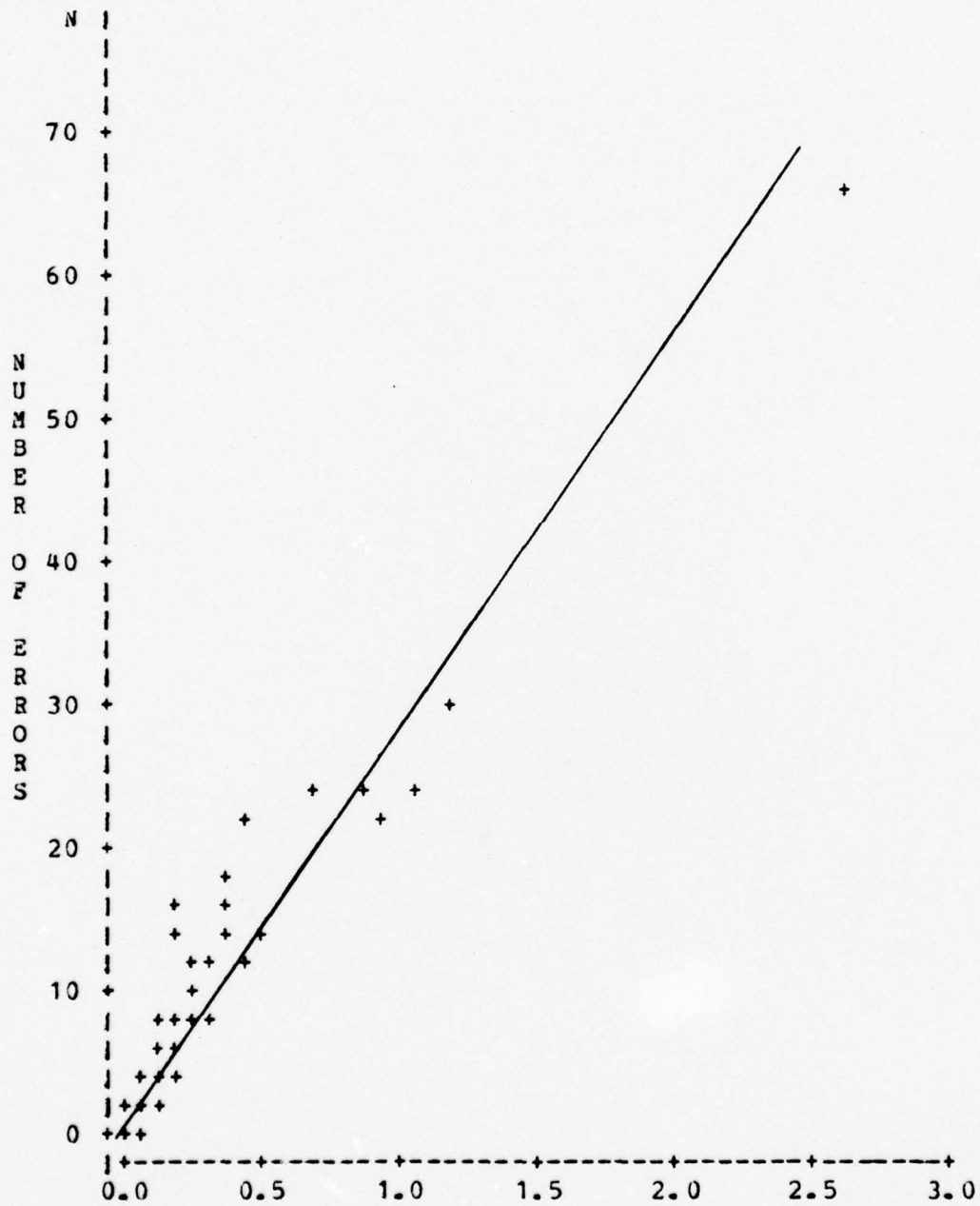
Figure 20. Plot of the Normalized Control Flow
Complexity Model for Project 3

VII. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Summary

The high incidence of errors in software is the underlying problem of software reliability. But, the most important unknown of software reliability is the number of residual errors in a program. If this number were available early in the software development stages, the software engineering process would be enhanced greatly. Several other unknowns could then be solved. One could determine when to stop testing a program, estimate the cost of maintenance and establish levels of confidence in programs and systems of programs, and develop more accurate software models that would model software failures more realistically. The results would be the ability to deal with all the unknowns of software reliability and reduce the overall cost of software.

The goals of this research were to determine if actual program characteristics are predictors of the number of errors in COBOL programs, to define program complexity measures from program characteristics, and to propose complexity models for predicting the number of errors in a COBOL program.

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Through simple linear and multiple linear regression analysis of 3 sources of data, the number of errors in a COBOL program was shown to be a function of its structure which can be measured by 22 characteristics metrics. A set of 13 unrelated characteristics metrics was selected from the 22 characteristics metrics to define 7 local complexity metrics. The 7 local complexity metrics were predictors of the number of errors in a program. Consequently, these metrics were used to estimate models to predict errors. The "best" single variable model for predicting errors is the Control Flow Complexity metric model. The "best" multiple variable model for predicting errors is the one that contains all 7 local complexity metrics. Analysis of Project 4 showed that the latter model can be used when dealing with many types of programs that are developed by different organizations. However, each organization should estimate the model parameters relative to error data from its development projects. Results relative to Projects 1, 2, 3 and 4 are summarized in Appendices B, C, D and E respectively.

There are several applications for the complexity models. Some of them are:

1) Estimating the number of errors in programs,

2) Controlling the quality and structural complexity of programs during design [18],

3) Estimating and allocating resources for program maintenance [15,62],

4) Estimating a level of confidence in a program [4],

5) Developing failure, density, and reliability functions
   for software reliability, and

6) Establishing a cut-off point for debugging and
   testing computer software [10].

Regardless of application, however, it is necessary to es-
timate the number of errors. Once this number is available,
the problems of software reliability can be treated more ef-
fectively. In order to illustrate the application of the
complexity model in determining software reliability, Appen-
dix F presents an example calculation for Project 2.

Conclusions

A detailed look at error types showed that logic and
data handling were, percentagewise, the most frequent errors
in Projects 2 and 1 respectively. However, when error data
from both projects were combined, logic errors were the most
frequent errors. It seems that the percentage of error
types will vary depending on type of software; but, in gen-
eral, logic errors will normally be the most frequent.

Twenty-two program characteristics metrics were
analyzed by regression analysis techniques. Both single and
multiple variable regression analysis showed that the rela-
tionship between the metrics and the number of errors was
significant. Both single and groups of the structural char-
acteristics metrics were good predictors of the number of
errors. The number of logical conditions is the "best"
single predictor. The number of unconditional branches is

the "second best" single predictor. Different combinations
of metrics were good predictors also. The metrics in the
"best" equations, as determined by the Maximum R-square
technique, varied by project. However, "LC" and "UBR" con-
sistently appeared in the "best" equations. Thirteen unre-
lated metrics were selected to measure program complexity.

Total program complexity is measured by 7 local com-
plexity metrics. Several complexity models are good predic-
tors of the number of errors in COBOL programs. The "best"
single variable model for predicting errors is the Control
Flow Complexity metric model. The "best" multiple variable
model for predicting errors is the one that contains all 7
local complexity metrics. The latter model can be used when
dealing with many types of programs that are developed by
different organizations.

Recommendations

One very worthwhile outcome of this study was a posi-
tive attitude toward being able to predict software errors
from complexity measures. This paper only scratched the
surface by showing that program complexity could be used to
predict the number of errors in COBOL programs. However,
the measures should apply to all languages. Other research
areas are discussed below.

The results from the error type analysis indicate that
error types did have some sort of distribution. Complexity

metrics for specific error types would be very useful for costing and scheduling program maintenance.

The Data Use metric seems promising. It seems that the Reserve Word characteristic metric is related to this metric. More research is needed to determine if this is true.

It was shown that the number of errors are predictable from complexity measures. We hypothesize that the number of personnel assigned to a development project, total software cost, total development time, computer test time, maintenance cost, and program enhancement cost are also functions of program complexity measures. Additional research is needed to determine if this hypothesis is true.

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APPENDIX A

Hardware Reliability Concepts

A brief summary of the more important concepts associated with the underlying mathematical reliability theory as applied to hardware is presented for those readers unfamiliar with reliability.

If a more detailed insight is desired then the reader should seek other references such as [69-71].

Introduction

The reliability of a component is defined as the probability that the component will function within specified limits for a specified period of time under specified environmental conditions. The frequencies at which components fail per unit time is called failure rate. Its reciprocal value is called mean-time-to-failure, abbreviated as MTTF. Several probability distributions are employed in the study of reliability.

Time-to-Failure Distribution

Let $f(t)$ be the probability density of the time to failure or malfunction of a component; that is, the probability that the component will fail between times t and $(t+\Delta t)$ is given by $f(t) \cdot \Delta t$. The probability that the compo-

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nent will fail sometimes before t is given by

$$F(t) = \int_0^t f(t)dt$$

which is sometimes called the "unreliability" function.

Reliability Function

The probability that a component will survive to time t is given by the reliability function

$$R(t) = 1 - F(t).$$

The reader should note the relationships between $f(t)$, $F(t)$ and $R(t)$. In particular

$$f(t) = dF/dt = -dR/dt.$$

Mean-Time-To-Failure

A measure of effectiveness often required in reliability is the MTTF. This is found by taking the first moment of the mean of the time to failure distribution. In terms of the density $f(t)$,

$$MTTF = \int_0^\infty tf(t)dt.$$

An equivalent expression giving the MTTF in terms of the reliability function is

$$MTTF = \int_0^\infty R(t)dt.$$

Instantaneous Failure Rate

The probability that a component will fail in the interval from t to t+Δt, given that it has survived to time t, is as follows:

$$P(t < T \leq t + \Delta t | T \geq t) = \frac{F(t + \Delta t) - F(t)}{R(t)}$$

dividing this expression by Δt yields an average rate of failure in the interval from t to t+Δt, given that it has survived to time t, as follows:

$$\left[\frac{F(t + \Delta t) - F(t)}{\Delta t}\right] \cdot \frac{1}{R(t)}$$

By taking the limit of the last expression as $\Delta t \rightarrow 0$, the instantaneous failure rate or hazard function H(t) is obtained; that is,

$$H(t) = \lim_{\Delta t \to 0} \left[\frac{F(t+\Delta t - F(t)}{\Delta t}\right] \cdot \frac{1}{R(t)} = \left(\frac{dF(t)}{dt}\right) \cdot \frac{1}{R(t)}$$

using the identities involving f(t), F(t) and R(t) we get the following equivalent expressions for H(t):

$$H(t) = f(t)/R(t)$$

$$= -\frac{dR(t)/dt}{R(t)}$$

$$= -\frac{d}{dt} \ln [R(t)].$$

This differential equation is solved for R(t) to yield

$$R(t) = \exp\left(-\int_0^t H(t)dt\right),$$

and since $H(t) = f(t)/R(t)$ we get

$$f(t) = H(t) \exp\left(-\int_0^t H(t)dt\right) \qquad (A1)$$

Expression (A1) shows that the time to failure density is related to the instantaneous failure rate function. Also (A1) is a general expression that applies to any type of failure density and hazard rate functions. Figure 21 shows a typical hazard function as a function of age.

The Exponential Model

There are situations where a component reaches a point in its life cycle where the failure rate is constant, that is,

$$H(t) = c, \quad c > 0.$$

On substituting into equation A1 we get the time-to-failure density

$$f(t) = c\exp(-ct), \qquad t > 0$$

which is the exponential probability density function, see Figure 22. Further calculations show that

$$R(t) = \exp(-ct)$$

and

$$MTTF = 1/c.$$

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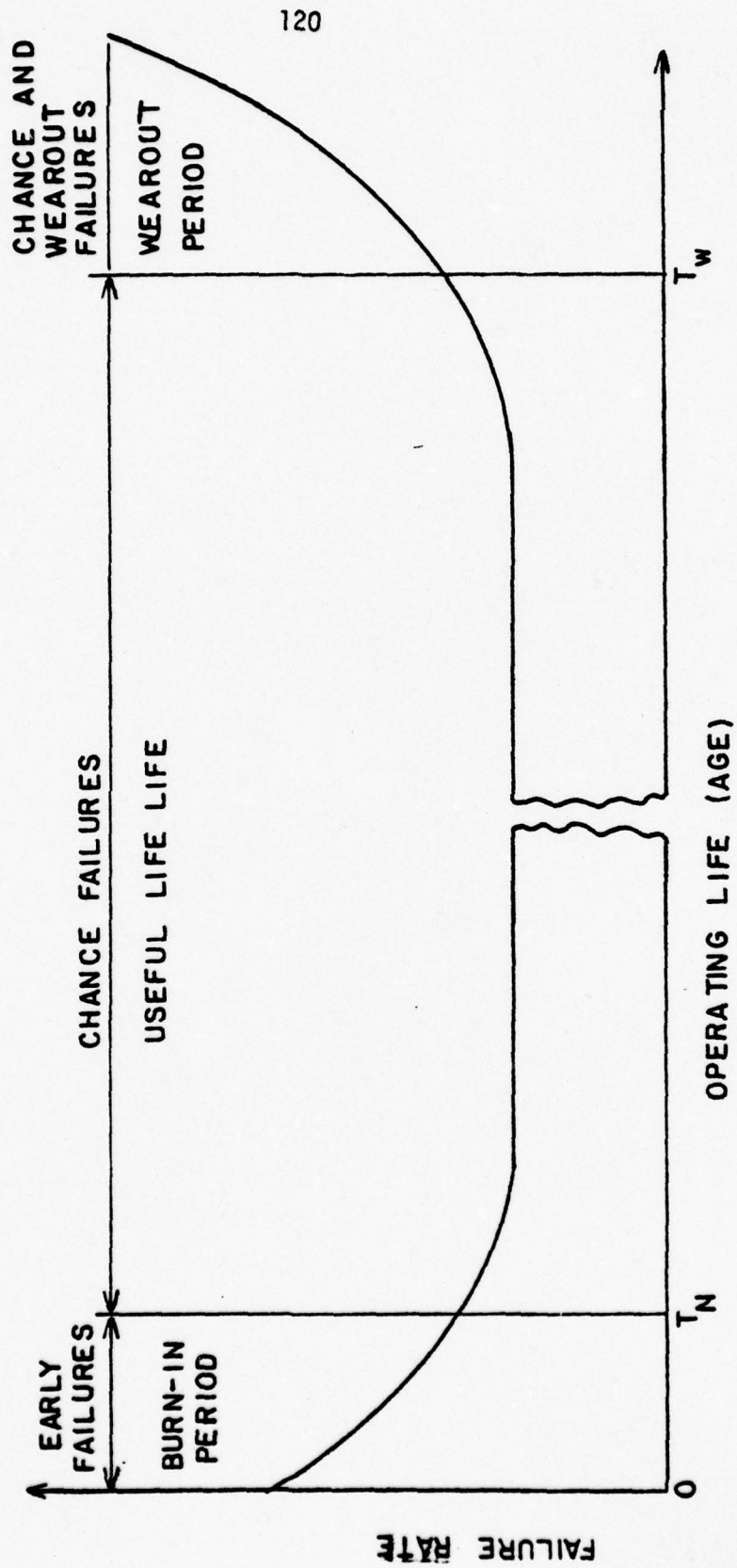
Figure 21. COMPONENT FAILURE RATE AS A FUNCTION OF AGE

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(a) Density Function

$f(t) = c\exp(-ct)$

(b) Reliability Function

$R(t) = \exp(-ct)$

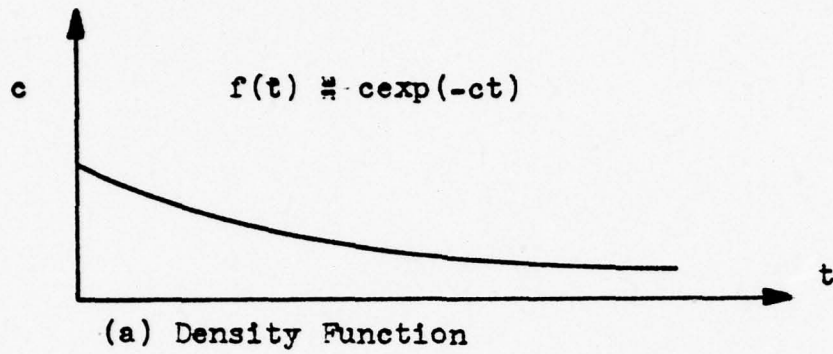(c) Hazard Function

$H(t) = c$
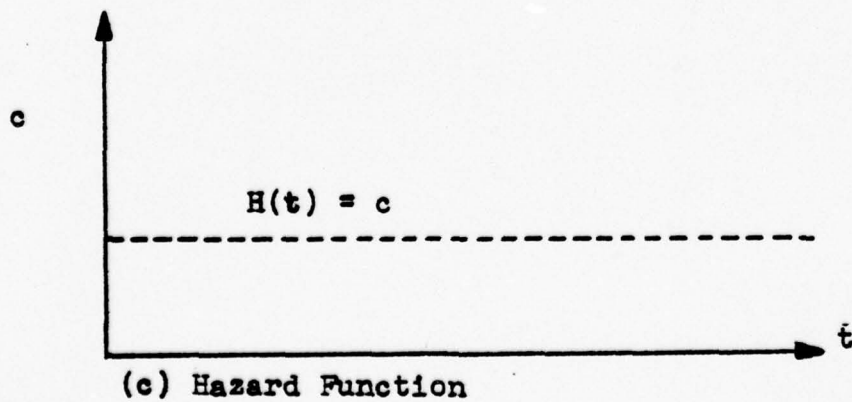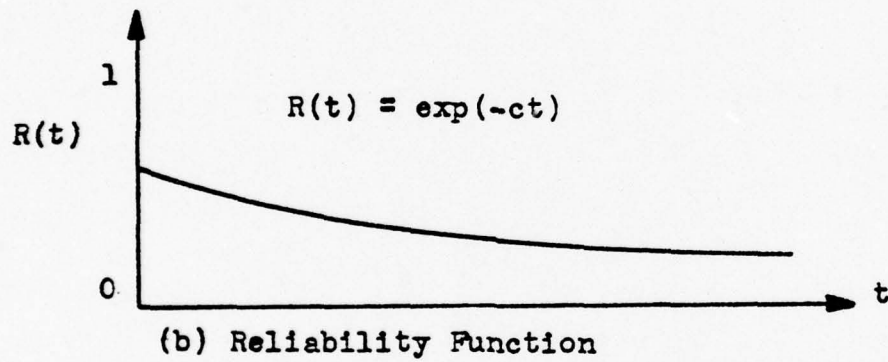
Figure 22. Exponential Distribution

The exponential model is the most widely applied model in reliability engineering. This is due to its simplicity and its theoretical properties such as constant failure rate and loss of memory property [70,71]. In many situations failures are described quite well by the exponential model, but there are also many examples where it is not appropriate.

The Weibull Model

The exponential distribution is a single parameter distribution which can be represented as a special case of a more general two-parameter distribution called the Weibull distribution.

The assumption of a constant failure rate is often appropriate for describing chance failures, but it is not always sufficient. This is particularly true during the early "burn-in" period and the late "wear-out" period in the life cycle of a component, see Figure 21. Nor would the constant failure rate be appropriate during a period of reliability growth due to improvements in the component. Thus, it is obvious that a function that allows an increasing or decreasing failure rate is required. The versatile Weibull function is often used to approximate such failure rates. The hazard function is

$$H(t) = \lambda B t^{B-1} \quad ; \quad t > 0 \quad ; \quad \lambda B > 0 \ .$$

When B < 1 the failure rate decreases with time; if B > 1 it increases with time; and if B = 1 the failure rate is constant, see Figure 23. The distribution and density functions are

$$f(t) = \lambda B t^{B-1} \exp(-\lambda t^B), \quad t > o$$

$$F(t) = \int_0^t \lambda B t^{B-1} \exp(-\lambda t^B), \quad t > o .$$

The reliability function is

$$R(t) = \exp(-\lambda t^B) .$$

The Weibull model enjoys widespread use because it can be justified theoretically and because it is so versatile.

Others Models

There are other probability functions which are useful for describing the random nature of failures. They are the normal, gamma, and lognormal.

$$\text{NORMAL:} \quad f(t) = \frac{1}{\sigma\sqrt{2\pi}} \; e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2} , \quad -\infty < t < +\infty$$
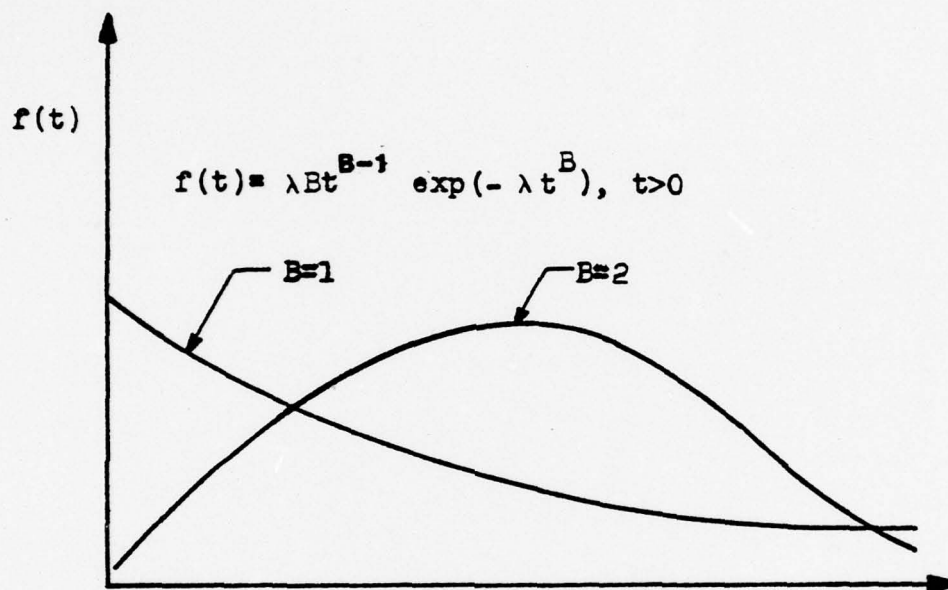
Figure 23. Weibull Density for B=1 and B=2

and

GAMMA: $f(t) = \dfrac{t^{\alpha-1} \exp(-t/B)}{\Gamma(\alpha)B^{\alpha}}$; $t, \alpha, B > o$

and

LOGNORMAL: $f(t) = \dfrac{1}{\sqrt{2\pi}\,Bt} \exp[-(\ln t-\alpha)^2/2B^2]$; $B > o$.

For appropriate choices of parameters, the gamma and lognormal functions can be made to represent increasing or decreasing failure rates. The normal function is primarily used during the wearout period of a component, see Figure 21.

APPENDIX B

Summary of Project 1 Characteristics

Description:

Project 1 is a data collection system. The system provides an on-going data base for input into reliability models. The data base also contains program characteristics as discussed in this paper. The system applies to COBOL programs designed to execute on the Honeywell H6060 computer system throughout the Air Force. The 5 programs in this system utilize a file management system available on the H6060.

Development Agency:

Air Force Data System Design Center; Gunter AFS, Montgomery, Ala.

Computer System: Honeywell H6060.

Operating Mode: Batch.

Number of Programs: 5.

Language: COBOL

Total Number of Lines of Source Code: 2280.

Best Single Variable Characteristics Metric Model:

$$\bar{N} = -1.683 + 1.047UBR.$$

Best Single Variable Complexity Model

$$\bar{N} = 0.287 + 0.382CFC.$$

Best Multiple Variable Complexity Model

$$\bar{N} = 3.156 + 0.326CFC - 0.017IOC + - 0.146IC$$

APPENDIX C

Summary of Project 2 Characteristics

Description:

Project 2 is an on-line system involving several kinds of data processing activities such as personnel management, accounting and finance, inventory etc. Only 14 programs are available for analysis.

Development Agency:

City of Montgomery Housing Authority, Montgomery, Ala.

Computer System: National Cash Register NCR8200.

Operating Mode: On-line.

Number of Programs: 14.

Language: COBOL.

Total Number of Lines of Source Code: 19045.

Best Single Variable Characteristics Metric Model:

$$\overline{N} = 3.731 + 0.319LC.$$

Best Single Variable Complexity Model

$$\overline{N} = 8.943 + 0.096CFC.$$

Best Multiple Variable Complexity Model

$$\overline{N} = -1.291 + 0.079CFC + 0.019IOC + 0.314DUC + 0.208COC$$
$$+ 0.005DHC + 0.056IC - 0.074SC$$

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APPENDIX D

Summary of Project 3 Characteristics

Description:

   Project 3 represents an initial delivery of a large on-
line Command Manpower Data System(CMDS). CMDS is a resource
accounting and management information system which supports
the Manpower and Organization function at Major Command
level throughout the Air Force. The programs perform a wide
variety of data processing activities, general purpose util-
ity, data retrieval, data maintenance, etc. The programs
utilize a file management system available on the H6060.

Development Agency:

Air Force Data System Design Center; Gunter AFS, Montgomery,
Alabama.

Computer System: Honeywell H6060.

Operating Mode: On-line and batch.

Number of Programs: 46.

Languages: COBOL, FORTRAN, and Assembler (only COBOL
programs analyzed but CALLS to, and interface errors with,
FORTRAN and assembly language programs were counted).

Total Number of Lines of Source Code: 54116.

Best Single Variable Characteristics Metric Model:

   $\bar{N} = 4.355 + 0.038LC.$

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<u>Best Single Variable Complexity Model</u>

$$\bar{N} = 4.069 + 0.024CFC.$$

<u>Best Multiple Variable Complexity Model</u>

$$\bar{N} = 3.094 + 0.022CFC + 0.008IOC + 0.044DUC - 0.017COC$$
$$+ 0.009DHC + 0.005IC - 0.005SC$$

APPENDIX E

Summary of Project 4 Characteristics

Description:

This Project is a combination of Projects 1, 2 and 3.

Development Agencies:

Air Force Data System Design Center; Gunter AFS, Montgomery,

Alabama and the City of Montgomery Housing Authority.

Computer Systems: H6060 and NCB8200.

Operating Modes: On-line and Batch.

Number of Programs: 65.

Languages: COBOL, FORTRAN, and Assembly.

Total Number of Lines of Source Code: 75441.

Best Single Variable Characteristics Metric Model:

$$\bar{N} = 8.807 + 0.065UBR.$$

Best Single Variable Complexity Model

$$\bar{N} = 6.789 + 0.254COC$$

Best Multiple Variable Complexity Model

$$\bar{N} = 2.845 + 0.029CFC + 0.093IOC + 0.495DUC + 0.119COC$$
$$- 0.007DHC + 0.028IC - 0.138SC$$

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APPENDIX F

Application to Software Reliability

Several models for predicting the number of errors in
COBOL programs are presented in this paper. The "best" mul-
tiple variable complexity model for Project 2 is used in
this appendix. The equation is

$$\bar{N} = -1.291 + 0.079CFC + 0.019IOC + 0.314DUC + 0.208COC$$
$$+ 0.005DHC + 0.056IC - 0.074SC, \qquad (F1)$$

for the range of source data values contained in Table 6.
But, how does equation (F1) apply to software reliability?
Basically, this equation offers a solution to the primary
problem in software reliability, that is predicting the num-
ber of errors in a program. Once this number is known, the
hazard, time-to-failure distribution, and reliability func-
tions can be derived. Also, the failure frequency and
mean-time-to-failure can be calculated, and stopping points
for testing programs can be established. To demonstrate how
this is done, the Jelinski and Moranda (JM) [42] model (the
hazard function was discussed in Chapter III) is used. The
basic assumtions of the JM model are:

    1) The amount of debugging time between error occurrences
    has an exponential distribution with an error occurrence

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rate or hazard function proportional to the number of errors remaining.

2) Each error discovered is immediately removed, thus decreasing the total number of errors by one.

3) The failure rate between errors is constant.

The hazard function is

$$H[t(i)] = K[N - (i - 1)]$$

$$= K[N - n] \qquad (F2)$$

where

N is the total number of initial errors in a program,

K is the proportionality constant,

t(i) is the i-th time debugging interval, i.e., the time
    between the i-th and the (i-1)-st errors discovered, and

n is the total number of errors found to date.

As was pointed out in Chapter III, the critical problem is to estimate N and K. Equation (F1) is used to estimate N and the following equation [42] is used to estimate k:

$$\bar{K} = \frac{n}{\bar{N}T - \sum_{i=1}^{n} (i - 1) \, t(i)} \qquad (F3)$$

where

n is the numer of errors found to date

and

$$T = \sum_{i=1}^{n} t(i) \text{ is the total test time from start of testing.}$$

From this one can obtain the time-to-failure distribution (density function)

$$f(t) = \bar{K} (\bar{N} - n) \exp [-\bar{K}(\bar{N} - n) t(i)]. \tag{F4}$$

The reliability function is

$$R[t(i)] = \exp [-\bar{K}(\bar{N} - n)t(i)]. \tag{F5}$$

The mean-time-to-failure (MTTF) is

$$MTTF = \frac{1}{\bar{K} (\bar{N} - n)}. \tag{F6}$$

Example Calculations

Program number (observation) 4 from Project 2 is used to illustrate the calculations. The observed number is 22 (see Table 6). It is assumed that 5 errors have been detected during 8 days of testing. Therefore, "n" is 5 and "T" is 8 time units. Each time unit is 1 day. The procedure for calculating reliability equations is:

1) Calculate $\bar{N}$ using equation (F1),

2) Calculate $\bar{K}$ using equation (F2), and

3) Calculate reliability statistics using reliability equations (F4), (F5), and (F6).

Calculating Distributions

1) For $\bar{N}$ where (see Table 6)

CFC = LC + UBR + STOP = 59 + 59 + 1 = 119

IOC = IO = 57

DUC = DR/TD = 6.3474

COC = CO = 53

$DHC = DH = 124$

$IC = OSC + CC + PC = 0 + 0 + 18 = 18$

$SC = (PAR - EXIT) + 1 = (22 - 9) + 1 = 14$

$\bar{N} = -1.291 + 0.079 \ (119) + 0.019 \ (57) + 0.314 \ (6.3474)$

$\qquad + 0.208 \ (53) + 0.005 \ (124) + 0.056 \ (18) - 0.074 \ (14)$

$\qquad = 22.8$

$\qquad = 23$ since $\bar{N}$ is an integer.

2) For $\bar{K}$ where

$n = 5$, $T = 8$ and $t(5) = 1$

$$\bar{K} = \frac{n}{\bar{N}T - \sum\limits_{i=1}^{n}(i-1)\,t(i)} = \frac{5}{(23)(8) - [0 + 1 + 2 + 3 + 4]}$$

$$= \frac{5}{184 - 10} = \frac{5}{174} = 0.0287/\text{day}.$$

3) The hazard function is

$$H(t) = \bar{K}\ (\bar{N} - n) = 0.0287\ (23 - n).$$

A failure curve for different values of n is shown in Figure 24.

4) The density function is

$$f[\,t(i)\,] = \bar{K}\ (\bar{N} - n)\ \exp\ [-\bar{K}\ (\bar{N} - n)\ t(i)\,].$$

$$= 0.0287(23 - n)\exp[-0.0287(23 - n)t(i)\,].$$

5) The reliability function is

$$R[\,t(i)\,] = \exp\ [-0.0287\,(23 - n)\ t(i)\,].$$

Reliability curves for different values of n are plotted in Figure 25. A few calculations were t(i) = 1 and n varies are shown below:
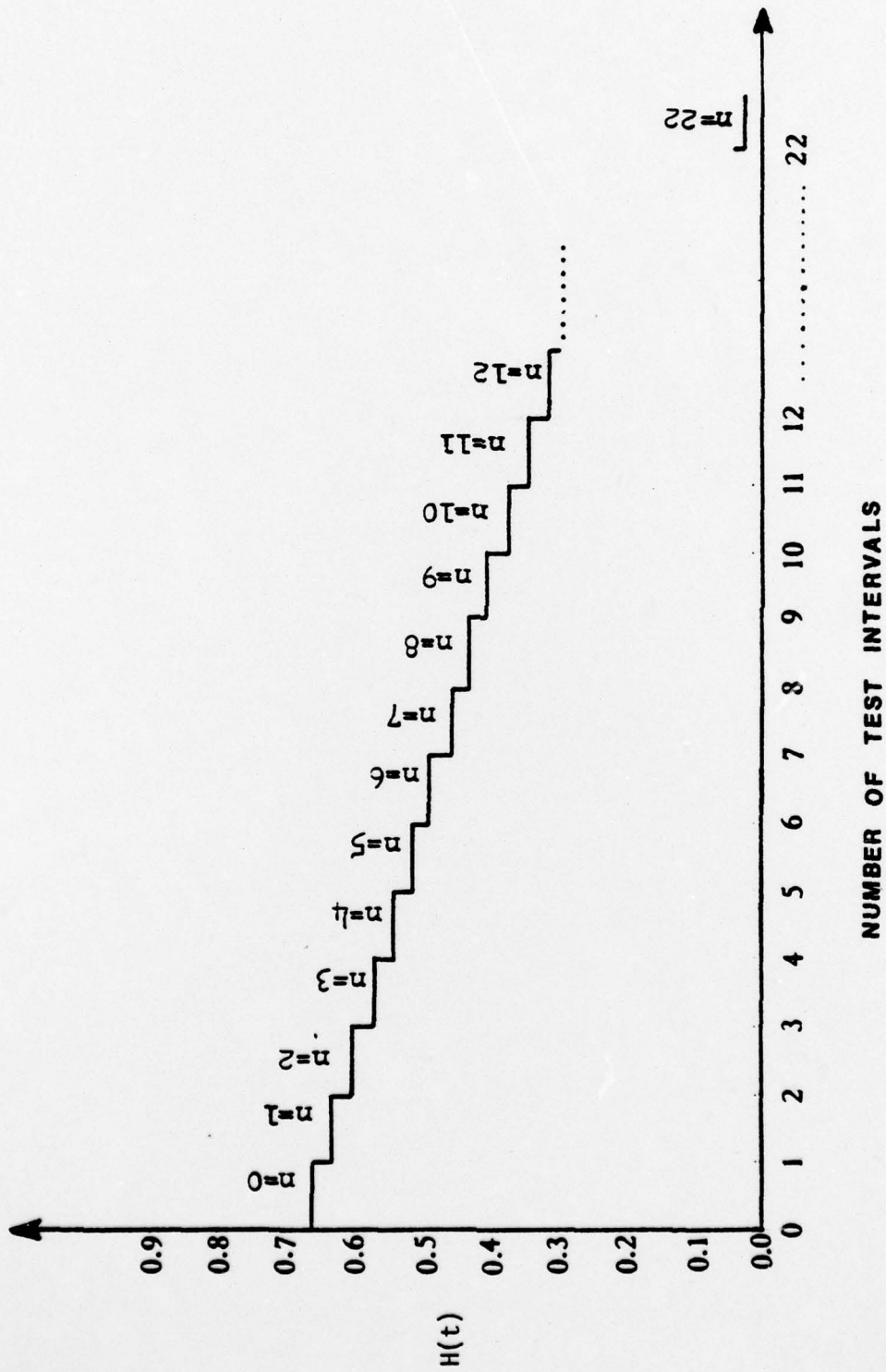
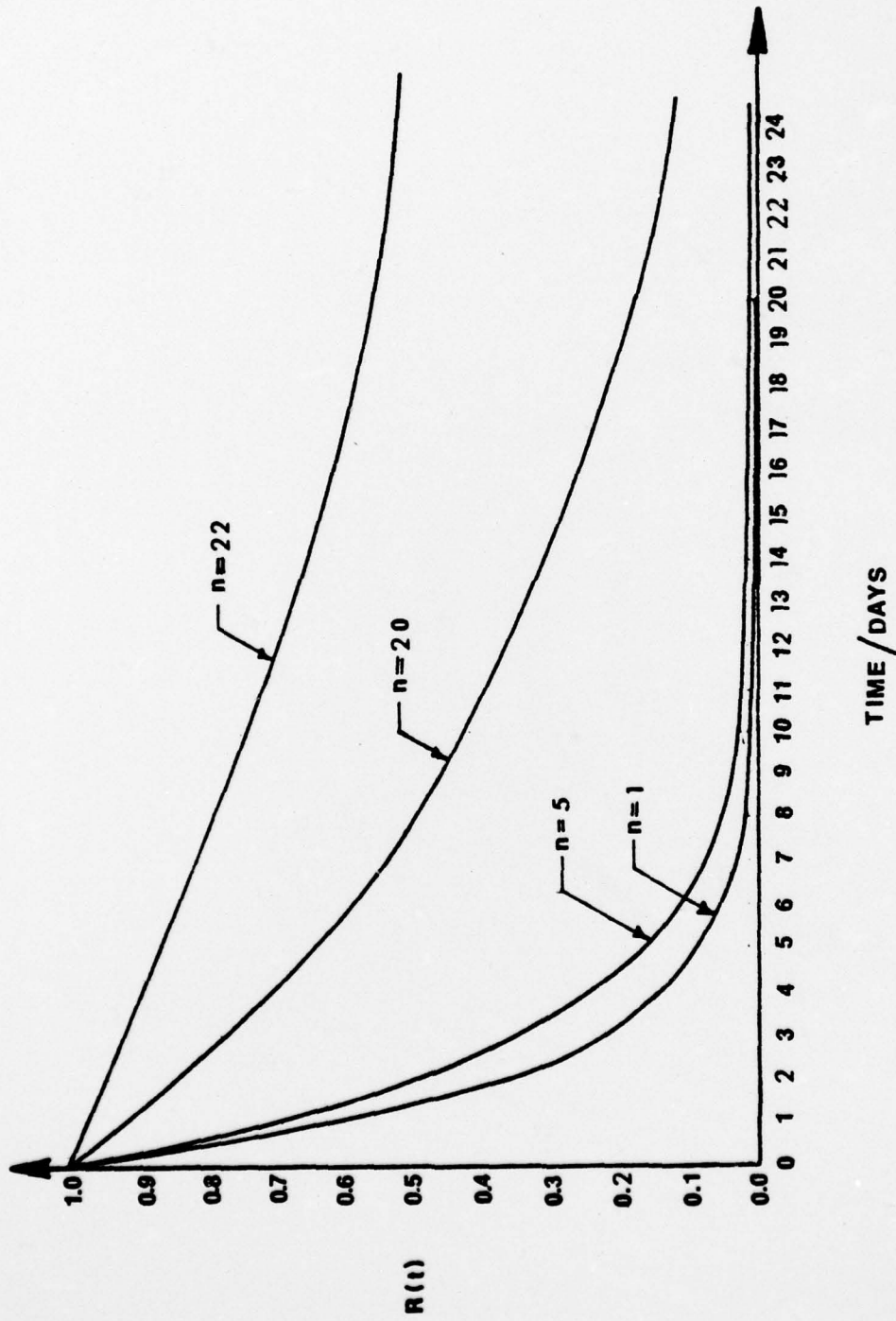NUMBER OF TEST INTERVALS

Figure 4. Failure Curve for Program 4 of Project 2

Figure 5. Reliability Curves for Program 4 of Project 2

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If $t(i) = 1$ and $n = 5$ then

$$R(1) = \exp[-0.0287(23-5)1]$$

$$= \exp[-0.0287(18)1]$$

$$= 0.5966.$$

If $t(i) = 1$ and $n = 10$ then

$$R(1) = \exp[-0.0287(23-10)1]$$

$$= \exp[-0.0287(13)1]$$

$$= 0.6886.$$

If $t(1) = 1$ and $n = 22$ then

$$R(1) = \exp[-0.0287(23-22)\ 1]$$

$$= \exp[-0.0287(1)\ 1]$$

$$= 0.9717.$$

6) The mean-time-to-failure is

$$MTTF = \frac{1}{K\ (N - n)} = \frac{1}{0.0287(23 - n)}$$

If $n = 5$ then

$$MTTF = \frac{1}{0.0287(23-5)} = \frac{1}{0.0287(18)} = \frac{1}{0.5166} = 1.94 \text{ days.}$$

Establishing a Stopping Point for Testing

A cut off rule for determining when to stop testing is simply when the reliability of the program reaches a desirable reliability for a specific time period. Let one assume that it is necessary for program 4 to operate 1 day with a reliability of 0.9, When should one stop testing the program? The answer is after n errors have been removed. Calculations for determining this number are shown below:

$$R[t(i)] = \exp[-0.0287(23-n)t(i)]$$

$$0.9 = \exp[-0.0287(23-n)(1)]$$

$$0.9 = \exp[-0.6601 + 0.0287n]$$

$$\ln 0.9 = [-0.6601 + 0.0287n]$$

$$-0.105 = -0.6601 + 0.0287n$$

$$-0.0287n = -0.6601 + 0.105$$

$$-0.0287n = -0.5551$$

$$n = 19.34$$

$n = 20$, since n is an integer.

Since $R = 0.9175$ for $n = 20$, one should stop testing the program after 20 errors have been removed.

The next question that one naturally asks is, "approximately how long will it take to remove 20 errors?" Assuming systematic testing procedures are used, a rough estimate is calculated by multiplying the MTTF by the number of remaining errors in the program.

If 5 errors have already been removed then

$$MTTF(20-5) = 1.94(15) = 29.1 \text{ days.}$$

This estimate should be updated as errors are removed from the program.