A Methodology for
Integrating Maintainability into Large-Scale Software
Using Software Metrics

by

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(ABSTRACT)

Maintainability must be integrated into software as early in the development life cycle as possible to avoid overwhelming maintenance costs at later stages. This research describes a methodology which assists in the development of maintainable systems and does so without disrupting industry standard development techniques. The process uses software metrics and iterative enhancement concepts to reduce the complexity of high-level language code, making it less error-prone and more maintainable. The experiment uses large-scale system software from a major software producer.

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I. Introduction

Software maintenance is recognized as the single most expensive factor in a software project's life. Estimates place the cost of maintenance from 50 to 70 percent of the total life cycle cost of a software system [HALD88]. A survey of software managers indicates that they realize the crucial role which maintenance plays in their budgets. They also stress the problem that user demands for enhancements and extensions is often overwhelming. A majority even agree that software maintenance is more important than new development [LIEB78].

Given that software development is necessarily guided by budget and time constraints, the criteria for internal software acceptance is often that it satisfy the requirements of specific tests. However, correct software according to the test plan does *not* guarantee good software in terms of maintenance or other quality factors [MYEG76]. Recognizing that quality cannot be assured by testing alone, software should be delivered to a set of requirements that include criteria other than test sets.

The bottom line is that maintenance is the largest financial drain in a software system's life cycle, and the creation of software must be approached from a perspective that minimizes maintenance costs. The control of software maintenance costs should begin long before the product is delivered to the customer. Unfortunately, the cost benefits of controlling maintenance at the development stage is difficult for software management to realize [MUNJ78].

Software maintenance can be defined as any post-release change to software. Swanson [SWAE76] divides maintenance tasks into three categories

based on the motivation for the changes required: (1) corrective maintenance, performed when errors have been found in the software; (2) adaptive maintenance, performed in response to changing needs of the users; and (3) perfective maintenance, performed to eliminate inefficiencies, enhance performance, or improve maintainability. All three types of maintenance require that someone, not necessarily a person familiar with the system, understand and manipulate the code.

Many techniques and criteria to promote maintainability have been proposed. The primary ones include structured design and implementation, guidelines on the use of data structures and parameters, information hiding, and appropriate documentation [LAMD88]. Used correctly, these techniques make programs easier to understand and modify. Simply put, certain software engineering concepts help to make source code less complex, and therefore more maintainable.

As the complexity level of a piece of software increases, the code becomes difficult to understand and is more likely to contain errors. Code containing errors must be modified, but that maintenance is non-trivial since the code is difficult to comprehend. To compound the problem further, it has been shown that programs cannot be made more maintainable by simply changing their code. Belady and Lehman establish that maintenance activities tend to *increase* the level of complexity of the code, so more maintenance is likely to be required [BELL76].

This snowball cycle is called the ripple effect of software maintenance which must be controlled at the earliest possible point in the life cycle [YAUS88]. Certainly, using software engineering techniques increase the maintainability of software, but they are difficult to measure and enforce. If maintainability is to be an expected consequence of software development, ways to measure it must become an integral part of the development cycle.

Software quality metrics, when defined and used correctly, have been shown to be good indicators of software complexity [CONS86]. Metrics are quantitative evaluations of software design or code based on some set of criteria which contribute to the software's complexity. If metric analysis results were required to conform to quality tolerances, the development process would not be compromised. Software metrics are discussed in greater detail later.

Maintainability is not an incidental result of other practices. It must be consciously integrated into a software project. Furthermore, deep-seated problems of maintainability require non-trivial solutions [MUNJ78]. This implies that the emphasis on controlling maintenance costs should shift toward the early stages of the development life cycle, as opposed to the post-production attention it currently receives.

Linger contends that a major problem with maintenance stems from a software management attitude which does not recognize software maintenance as a mature discipline [LINR88]. Software managers must realize that knowledgeable use of state-of-the-art tools and techniques will cause software to serve as well as survive.

This research is designed to explore the use of specific implementation techniques and tools to reduce the effort, and therefore the cost, required by the maintenance tasks of large-scale software projects.

II. Maintenance and the Software Life Cycle

Overstreet, et al. give an overview of the various software life cycles presented in current literature [OBRV86]. Software life cycle models describe the evolution of software systems as they are developed, implemented and

maintained.

Probably the most popular life cycle is the waterfall model characterized by Boehm [BOEB76]. In this model, the various stages of evolution are defined as a series of steps beginning with system requirements and proceeding through preliminary and detailed designs, coding and debugging, testing, and finally operations and maintenance. Each stage is validated, and as problems are identified, previous steps are repeated as necessary.

Another model, the automation-based paradigm, incorporates program transformations from requirements-based prototypes into fully operational systems using automated techniques [BALR83]. The transformations involve repeated iterations of validation and maintenance of specification to create the final system. All of the technology needed to support this model does not yet exist, but it offers an important view of the software development process.

The two-leg model describes the process of abstracting the formal specification of software down two paths providing both an application concept and an operational system [LEAM84]. The path to the operational system is called reification and incorporates a backtracking concept for required modifications.

Boehm proposes the spiral model, incorporating refinements to the waterfall model [BOEB86]. The spiral model provides risk analysis at each stage of development which is represented by an outward spiral. Cumulative cost is represented by the radial dimension of the spiral, and the angular dimension represents the progress made in completing each stage of development.

Maintenance plays a consistent role in all of these models. An understanding of the development and maintenance processes which a

software system endures throughout its existence is necessary in order to understand the proper point at which to consciously introduce maintainability.

According to the waterfall model, shown in Figure 1, and consistent with most industry development strategies, software is designed and implemented, then tests are run to verify that the software performs correctly. If the tests find errors, the code is corrected; or if an error is determined to stem from a design flaw, the design is modified, then the code is reimplemented. The tests are then run again. Finally, the system is released for consumer use. When errors are found by the users, a maintenance task is initiated to fix the problem. Once the problem is addressed, the software is reissued to the consumers, who are then likely to find additional or new problems.

Some effort has gone into the process of easing the maintenance tasks at the post-production stage. Cashman and Holt [CASP80] describe a communication-oriented system called MONSTR (MONitor for Software Trouble Reporting) which is designed to structure the environment for software maintenance. The system formulates the manner in which problems are reported, analyzed and solved based on communication protocols.

Selby and Basili describe a technique to localize errors during a maintenance activity by analyzing the source code [SELR88]. Measurements of data interaction, called data bindings, are used to estimate software coupling and cohesion. From these, a hierarchial description of a software system is obtained which helps determine error location.

Maintenance problems will never completely be eliminated and therefore such efforts are often helpful. However, concentrating on maintenance problems at the post-production stage is analogous to closing the barn door after the horse has escaped. Studies have shown that the earlier in

Figure 1. The classic waterfall model of software development.

the life cycle that errors are corrected, the less costly they are [LIPM79]. Therefore, the earlier that controls on the complexity of software are enforced, the less costly the error correction effort will be. The natural conclusion is to control software complexity at the time of its design.

Henry and Selig have demonstrated that it is possible to analyze software systems at the design stage under automated control [HENS88]. Using a programming design language (PDL) which can be statically analyzed with a software tool, student programs were evaluated with software quality metrics to determine complexity violations. These metrics correlate well with the metrics obtained from the actual code produced at implementation time. They also generate equations to predict source code quality from a PDL design.

Unfortunately, few software managers will deviate from their normal life cycle processes to accommodate the extra calculation of software metrics. PDL's such as the one used in Henry and Selig's research are syntactically specific and often require more time than necessary to communicate the same information in other ways. For realistic usage, the control of software complexity should disrupt as little of the current life cycle as possible.

Similar work shows that graphical design languages, which can more clearly communicate design details than text-based PDLs, can also be evaluated using metrics tools [HENS87]. Once again, however, a disruption of existing industry design processes is necessary to incorporate this technique unless the required software and hardware are already in use. Unfortunately, the main 'stream design techniques used in industry today do not lend themselves to automated evaluation.

Given that current design evaluation techniques are impractical, the next level of the life cycle can be investigated: implementation. All logic is eventually implemented and tested. Furthermore, high level language code is

already syntactically specific. Therefore, code analysis at this stage is possible without disrupting the normal flow of software design and implementation. For large-scale software development, this analysis still produces results that can be used immediately.

Figure 2 shows a modified software development life cycle, integrating the code analysis into the basic waterfall model. In this scenario, as testing occurs, the code is analyzed to obtain complexity measures. Then, when changes are made in the design or code for error reasons, changes are also made that embrace the goal of reducing the complexity of the sections of software found to be above set complexity tolerances. Furthermore, since test results are indicative of quality to the degree that test cases exercise software attributes, the complexity measures are used to guide test case planning.

When referring to software development in industry, it is also important to realize that large-scale software projects often involve hundreds of thousands of lines of code, and that the simple life cycle presented so far does not capture the details of the process. To produce a practical methodology for integrating the use of metrics, these details must be taken into account. This is thoroughly discussed in Chapter 5.

Software metrics have been used quite successfully in the past as complexity measurements, and fit well into the scheme described here. It is now important to understand more about the use of software metrics.

III. Software Metrics

Software metrics are measurements of code complexity based on some set of characteristics of the code, providing a relative, quantitative evaluation [CONS86]. Some metrics concentrate on the amount of syntactic entities which

Figure 2.   Metric analysis in the software development process.

must be understood in a procedure, and are called code metrics. Structure metrics are concerned with the structure of the software system being analyzed, including the quantity of information transferred among procedures. Still other evaluations combine the concepts of code and structure metrics. These are called hybrid metrics.

The metrics used in this study are fully described in Chapter 2, including how each is calculated and the exact characteristics each attempts to measure. It is very important that any use of a metric be accompanied by careful consideration of what that metric actually indicates about a procedure's complexity. For example, metrics which concentrate on length factors do not imply anything about the complexity of the communication between that procedure and other procedures, and vice versa.

There is no one metric that tells the whole complexity story about arbitrary source code, therefore several metrics are used in this research. Hybrid metrics, which combine several evaluations, are often better indicators for the same reason. Studies have indicated that no single metric is sufficient for indicating complexity [CANJ85].

Metrics can also be inconsistent among source languages, applications, or operating environments. A certain metric might be a very good indicator for one language because of certain structures or capabilities, but be mediocre for another. Similarly, a metric might be a good complexity indicator in a particular operating environment, but not as informative in another type of environment. Therefore, it is important to validate the metrics results to determine which metrics are best for a given language and system environment, and to understand why others do not yield such good results.

Calibration of metrics is also necessary. That is, certain tolerances should be determined for each metric, indicating that the procedures whose

metrics fall out of this range are potential problems. Using tolerance levels is safer than a judgement based on a relative average across procedures since a large number of procedures in a system could have complexity levels above that which is actually reliable.

This calibration process is unspecific, and the values may be modified many times after the initial estimate. As the metrics are further used and understood in a particular environment, better judgements can be made concerning the safe metric tolerances.

Kafura and Reddy establish the link between the use of software metrics and the efforts of software maintenance [KAFD87]. The study explores medium-sized software systems and uses the informed input of experts who were intimately familiar with the system to validate the metric results. Kafura and Reddy conclude that the software metrics agreed with the general maintenance tasks required, that the metrics identify improper integration of functional enhancements, and that the metrics agree with the expert subjective understanding of the system.

Wake and Henry perform a similar study using software quality metrics on a small sample of production code from a major software vendor [WAKS88]. Using a maintenance history describing the modifications made to the code, Wake develops regression equations which successfully predict the need for maintenance in specific sections of the software. The equations calculate the predicted number of errors and predicted number of lines changed based on metric values.

Given the use of software quality metrics as a tool for integrating maintainability into large-scale software, we must now briefly address the current experiment.

IV. Research Data

This research is based on software designed and implemented by a major commercial software developer. The software is written in a high-level, in-house language called Mesa, which supports real-time, concurrent system activity.

Three important aspects of this research should be stressed. The first is the use of objective error data on which to base the results of the metrics validation. Second is the use of an automated tool to perform the metric collection. The third aspect is the use of realistic, large-scale data for the metric analysis, instead of the commonly seen test bed of student programs.

Within this study's software development scheme, distinct internal releases of the software are frozen for system testing and progress identification purposes. This research evaluates the code at a mid-development release point using software quality metrics to see if they correspond to actual modification needs as determined by the normal testing procedures. If the metrics identify the points at which maintenance is required, then the relationship would indicate that this technique is recognizing error-prone software.

Therefore, if code enhancement is performed as a result of metric analysis to reduce code complexity, fewer maintenance tasks would be required, and test cases concentrating on the highly complex code would uncover more errors. Furthermore, the inevitable maintenance tasks that are required eventually would be easier to handle because the complexity of the code is reduced.

V. Conclusion

Given the expensive nature of software maintenance, specific steps must be taken to reduce maintenance costs at some point in the software life cycle. Studies have shown that software which is highly complex is also error-prone and difficult to maintain. Therefore a process which controls the complexity of software reduces the maintenance effort.

Dealing with maintenance costs during post-production modifications only treats the symptoms, not the cause. However, for practical usage, disruption of industry standards for software development and testing must be avoided. Therefore, an appropriate point in the life cycle to consciously reduce software complexity and integrate maintainability is during the iterative cycles of error testing and functional enhancement.

The goals of this research are: (1) Design and implement a metrics collection tool for the Mesa language; (2) Validate that the metrics calculated by the tool indicate error-prone software; (3) Establish regression equations which predict the number of errors that are present in a section of code; and (4) Develop a methodology using these tools and techniques which integrates maintainability into large-scale software. This methodology must be as unobtrusive as possible so that it can be practically used.

This research uses an automated tool to collect software quality metrics on arbitrary source code. These measurements can direct where effort should be expended to make the code less complex and where additional testing is required. The study is performed on large-scale, real-time software written in Mesa, a system development language.

Chapter 2 describes in detail the metrics used in this study. This includes the manner in which they are calculated and what information can be determined from each metric. Chapter 3 describes the Mesa language and explains the metrics collection tool, the types of data collected, and the levels

of detail at which the data was collected. Chapter 4 contains the analysis of the data from one internal release of the software. Chapter 5 describes the methodology for integrating maintainability into large-scale software development. Finally, Chapter 6 reports the conclusions of this study and discusses possible future work.

Chapter 2: Software Metrics

I.   Introduction

Over the past several years, software metrics have been shown to be valuable indicators in the quantitative evaluation of software and software designs.   Code which is complex is more likely to have logical errors.   Once errors are found, the high complexity also makes the code more difficult to correct.   Therefore complexity has a direct effect on maintenance.   The metrics described here are designed to quantify the level of complexity of a piece of code.

For any measurement to be useful, it is important to understand exactly what that measurement means and how to calculate it correctly.   This chapter is an overview of the metrics used in this study and a discussion of what kinds of information can be determined from each.

The metrics used in this study were chosen for specific reasons.   Of the many software metrics that have been proposed, only those which are totally automatable were considered.   The amount of data in this analysis immediately disqualifies any subjective evaluation of the code, or even any objective evaluation that requires individual attention or time-consuming processing.

The metrics discussed here are based on a static analysis of source code. No measurements are made pertaining to the run-time execution of the software.   The metrics are discussed here at the procedure level, defined as a small collection of programming statements.   Grouping procedures into higher levels of abstraction is discussed later.

Software metrics can be subdivided into three areas: code metrics, structure metrics, and hybrid metrics. Each class is now discussed and the metrics from each explained.

II. Code Metrics

Metrics which deal only with the amount of substance a given procedure contains are called code metrics. The underlying theory is simply that the more items requiring attention that exist in a procedure, the harder that procedure is to understand. A code metric measurement tends to identify the internal quality of a procedure.

Three types of code metrics are analyzed in this study. They are lines of code[CONS86], Halstead's Software Science indicators[HALM77], and McCabe's Cyclomatic Complexity [MCCT76].

Lines of Code

One popular metric is the measure of how many lines of code (LOC) exist in a given procedure. The intuition is that a procedure with twenty LOC, for example, is considerably less complex than one with fifty LOC. Most software engineers agree that the overriding consideration concerning the length of a procedure is that it perform a solitary function. This can usually be accomplished in less than fifty lines of source code [MYEG76].

The LOC metric becomes useful in the immediate identification of flagrant violators of certain complexity and modularity tolerances. When analyzing a software system whose average LOC per procedure is thirty (an established norm), a particular procedure measuring one hundred lines of code instantly warrants attention. That procedure should be extremely

straight-forward at first glance, and even then most software engineers would dictate that it should be modularized further.

However, the LOC measurement is a simplistic view that immediately raises several concerns. First, it should be obvious that not all code statements are of equal complexity. The LOC metric ignores the type of statements being counted and only relies on a gross measure of volume. Procedure A with twenty straight-forward output statements cannot possibly be as difficult to understand as procedure B with twenty statements involving multiple nested loops, complicated boolean conditions and a high degree of computation. Yet the LOC measure indicates that these two procedures are equally difficult to comprehend.

Another problem with the LOC metric stems from the definition of a single line of code. Researchers have not agreed on how to count a line of code, though most agree that the measurement should not include blank lines or comments. They also debate whether variable, type, and constant declarations should be considered in the LOC count [CONS86].

Some researchers promote counting any source code line which contains a portion of source code. The trouble with this view is that programmer style becomes an issue. In high level languages such as Pascal or 'C', where end-of-line markers are not delimiters, a source code statement could be spread over ten lines in the file, or it might be kept on one line. The LOC measure would indicate a large difference in complexity from code that is identical, merely spaced differently.

Another method of counting lines of code is to use some token from the source language which acts as a line terminator or separator. In Pascal and 'C', the semicolon character serves this purpose. This way, no matter how spread out a single source code line is in the file, the counts are the same.

In general, if the research in question deals with a large enough data sample, it is sufficient to choose a method and be consistent with it's use. Programmer idiosyncrasies tend to offset one another and a valid measurement is obtained. In the Mesa analysis, the use of the semicolon character as a statement separator is similar to its use in Pascal, therefore a semicolon count is used to determine the LOC measurement. Given the complexity and versatility of Mesa declarations, they are also counted.

Halstead's Software Science

Another set of popular code metrics is defined by Halstead [HALM77]. His measurements are based on the counts of operators and operands within a body of code. The following four initial values are calculated for a procedure:

$n1$ = number of unique operators

$n2$ = number of unique operands

$N1$ = total number of operators

$N2$ = total number of operands

In making these measurements, everything in the source code is considered to be either an operator or an operand. Operands consist of any entity being operated upon, such as constants and variables. Operators consist of all other items in the procedure. These include arithmetic and boolean operators, control statements, and assignment structures. Distinct keywords which cooperate to perform one function are often logically grouped and considered to be one operator, such as the If-Then, While-Do, and Begin-End constructs. The constructs considered as Mesa operators are given in Appendix A.

Once these initial counts are taken, the following values are defined:

$$n \quad = \quad n1 \quad + \quad n2 \qquad \text{Vocabulary Size}$$

$$N \quad = \quad N1 \quad + \quad N2 \qquad \text{Length}$$

Since every entity is included in the counts as either an operator or operand, the sum of the unique elements is called the vocabulary size, and the sum of the total count of elements is considered to be the length, or total number of tokens, of that procedure.

Given these definitions, Halstead then defines program volume, program level, language level, and effort.

Program Volume

Program volume is a measure of size based on the length of the implementation and the size of the vocabulary. Given **n** distinct elements, the smallest binary representation of a particular element requires $\log_2(n)$ bits. Therefore the program volume can be expressed by the following formula:

$$V \quad = \quad N \quad x \quad \log_2(n) \qquad \text{Program Volume}$$

The program volume can also be interpreted as the number of mental comparisons needed to generate the program code. This view assumes that a programmer selects an element by making a mental binary search through the program vocabulary. This interpretation is important in the derivation of the formula for effort.

A related measurement, the potential volume V^*, is defined as the size of the most succinct form in which a particular algorithm could ever be expressed. This value cannot be determined without prior existence of a language in which the necessary operations were implemented. The concept of potential volume is needed for the next measurement of interest, program level.

Program Level

The level of the code in which an algorithm is implemented is defined as the potential volume divided by the measured program volume:

$$L \quad = \quad V^* / V$$

Since V^* cannot be directly determined, an approximation for L is needed.

The minimum number of operators is two, consisting of a function designator and an assignment. There is no upper limit on the number of operators. Therefore, with respect to operators, program level may be approximated:

$$L \quad \sim \quad 2 / n1$$

Operands, however, have no lower bound. Intuitively, as operands are repeated, the implementation can be considered at a lower level. Then with respect to operands, the program level equation is:

$$L \quad \sim \quad n2 / N2$$

Halstead combines these ratios to yield an estimator for program level:

$$L = (2 / n1) \times (n2 / N2) \qquad \text{Program Level}$$

Program level is considered inversely proportional to program difficulty. The lower the level, the more difficult it is to implement the algorithm.

Language Level

Given any algorithm translated from one language to another, as volume increases, the program level decreases proportionately. Therefore, the potential volume, V^*, is the product of the program level and volume, which is seen from a simple algebraic manipulation of the first definition of program level:

$$V^* = L \times V \qquad \text{Potential Volume}$$

However, when the language is held constant and the algorithm changes, it is the potential volume which varies proportionately with the program level. Therefore, the language level is defined as:

$$lambda = L \times V^* \qquad \text{Language Level}$$

Substituting (L x V) for V* yields a computable value for language level:

$$lambda = L (L \times V) = L^2 \times V$$

The language level computation is a quantitative evaluation for comparing two different languages, which has previously been a subjective process.

Effort

The final Software Science metric analyzed is Halstead's effort, which attempts to quantify the effort required to generate the implemented code. Since the volume of the program dictates the number of mental comparisons needed to implement the program, and the program level is the reciprocal of the difficulty, the effort required can be expressed as:

$$E \quad = \quad V / L \qquad\qquad Effort$$

The effort calculation is the fundamental metric considered when using Halstead's Software Science for complexity analysis.

McCabe's Cyclomatic Complexity

A third code metric used in this study is defined in [MCCT76]. McCabe's cyclomatic complexity is defined as a count of the independent logical paths through a procedure. Intuitively, the more logical branches that a procedure contains, the more difficult it becomes to trace all possibilities of actual execution.

Based in graph theory, the complexity measurement is taken from a representation of a procedure as a strongly connected graph. Each node in the graph represents a sequential block of code, and each arc represents a logical branching point through the procedure. The graph must have unique entry and exit points.

Graph theory states that, given a strongly connected graph G with one component, the maximum number of linearly independent circuits V(G), also known as the cyclomatic number, is calculated:

$$V(G) = E - N + 2 \qquad \text{where}$$

$$E = \text{Number of edges in the graph}$$

$$N = \text{Number of nodes in the graph}$$

Therefore, McCabe defines cyclomatic complexity to be the cyclomatic number of a procedure's strongly connected control graph.

An alternative method of calculating cyclomatic complexity is used if the analyzed code is given in structured form. In this case the cyclomatic complexity is equal to a count of the number of decision points in a procedure plus one. In the graph representation, a decision point is any node which has more than one directed arc from it.

This alternative method allows for efficient calculation of the metric based on the source language constructs. Appendix B contains a list of the Mesa constructs used as logical branch indicators for McCabe's Cyclomatic Complexity calculation.

Figure 3 shows a strongly connected program control graph for structured code. An imaginary arc is added from the exit point back to the starting point so that the graph is strongly connected. This does not change the concept or function of the graph, and is not included in the calculation. Using either method described above to calculate the complexity gives the result V(G) = 4.

$$V(G) \ = \ E - N + 2 \qquad V(G) \ = \ DP + 1$$
$$= \ 12 - 10 + 2 \qquad \quad = \ 3 + 1$$
$$= \ 4 \qquad \qquad \qquad \quad = \ 4$$

Figure 3. McCabe's Cyclomatic Complexity calculation.

III. Structure Metrics

Another class of metrics, structure metrics, are all based in some way on the overall structure of the system being examined. These quantitative evaluations reflect the bigger picture of the programming system structure. The structure metrics examined are Henry and Kafura's Information Flow metric and Belady's Cluster metric [HENS81a] [BELL81].

Henry and Kafura's Information Flow

The structure metric developed by Henry and Kafura is based on the amount of information which flows in and out of a procedure. Formally, Henry and Kafura define two quantities, fan-in and fan-out:

fan-in: The number of local flows into a procedure plus the number of global data structures from which a procedure retrieves information.

fan-out: The number of local flows from a procedure plus the number of global data structures which the procedure updates.

To calculate these values, structure data is generated representing the flow of information within a routine from input and output parameters, global data structures, and return values from functions. Using these relations, a flow graph is constructed representing all possible paths through a program which result in updates of global data structures.

The complexity of procedure **p** is now defined as follows:

$$C_p = (\text{ fan-in } \times \text{ fan-out })^2 \qquad \text{Information Flow}$$

The product of fan-in and fan-out is squared because the complexity between system components is non-linear.

Belady's Cluster Metric

Belady discusses the complexity of a software system in relation to how it can be subdivided into logical sections called clusters based on the communication that exists among the individual components [BELL81]. He hypothesizes that understanding interconnected elements is more difficult if their number is large. Furthermore, given the elements, complexity is proportional to the number of connections.

The cluster metric calculation is based on a graphical representation of the system, where nodes of an undirected graph represent individual elements (procedures, files, etc.) of the system, and edges represent a communication line between the elements.

The complexity of an individual cluster of elements j is given as:

$$C_j = N_j \times E_j \qquad \text{Cluster Metric}$$

where N_j is the number of nodes within a cluster and E_j is the number of edges between those nodes.

Belady goes on to define the complexity of the entire system as the sum of the individual cluster complexities plus the quantity representing the intercluster communication complexity. That calculation is:

$$C = \sum C_j + (N \times E_0)$$

where N is the total number of nodes in the entire system, and E_0 is the number of intercluster edges.

Belady's calculation of software complexity is performed at higher levels of data abstraction than other metrics. This higher level makes it a particularly attractive measurement when dealing with large-scale systems.

IV. Hybrid Metrics

Code metrics are based on the volume of material that make up a given procedure. Structure metrics take into account the procedure as an entity in the entire system. The concept of a hybrid metric combines both types of evaluations. Any arithmetic combination of code and structure metrics is considered a hybrid metric, although many such combinations do not make intuitive sense.

Many hybrid metrics were considered in this study, including various code metrics weighting the Henry and Kafura Information Flow. Woodfield's Review metric is defined as a hybrid and is also considered [WOOS80]. The Information Flow structure metric was originally defined as a hybrid metric with LOC weighting the Information Flow value. Further research determined the Information Flow value was a worthwhile measure by itself and is presented here accordingly [HENS81a]. The following section describes Information Flow weighted by lines of code and Woodfield's Review Complexity.

LOC and Information Flow

Using the LOC count to weight Henry and Kafura's Information Flow metric yields the following definition of the complexity of an arbitrary procedure **p**:

$$Cp = LOC \times (\text{fan-in} \times \text{fan-out})^2$$

LOC, fan-in and fan-out take on their original meanings as defined above. Any code metric could replace the lines of code count to yield another hybrid version of the Information Flow metric.

Woodfield's Review Complexity

Woodfield's Review Complexity metric is based on the number of times a component of a system needs to be reviewed to completely understand the system [WOOS80]. Two types of connections between procedures are defined. A control connection exists between a procedure and the procedure which invoked it. A data connection exists between two procedures p and q if there is some variable V such that the following conditions hold:

1. The variable V is modified in **p** and referenced in **q**.

2. There exists at least one data path set D(p q), between **p** and **q**, such that the same variable V is not referenced in any d_i where d_i is a member of D(p q).

A data path set D(p q) is defined as an ordered set of one or more procedures $\{d_1, d_2, d_3, ..., d_n\}$ such that one of the following conditions hold:

1. **q** calls d_1; d_1 calls d_2; ... ; d_{n-1} calls d_n; d_n calls **p**.

2. **p** calls d_1; d_1 calls d_2; ... ; d_{n-1} calls d_n; d_n calls **q**.

3. There exists some d_i in D(**p q**) such that d_i calls both d_{i-1} and d_{i+1}; d_{i-1} calls d_{i-2}; d_{i-1} calls d_{i-3}; ... ; d_2 calls d_1; d_1 calls **q**; and also d_{i+1} calls d_{i+2}; d_{i+2} calls d_{i+3}; ... ; d_{n-1} calls d_n; d_n calls **p**.

Woodfield then defines fan_in of a procedure as the count of all control and data connections for that procedure. The complexity of procedure **r** is given by:

$$C_r \quad = \quad \text{Effort} \quad x \quad \sum \quad RC^{k-1} \quad \text{for} \quad k \ = \ 2 \ \text{to} \ (\ \text{fan\_in}_i \ - \ 1 \ )$$

Effort is the code metric defined in Halstead's Software Science. RC is a review constant, given as two-thirds in Woodfield's model. This constant was also suggested by Halstead [HALM77].

V. Conclusion

The metrics described in this chapter form the fundamental framework around which this study is based. Correct calculation of the metrics provides a quantitative method for evaluating software to determine which procedures are the most complex. Once identified, these procedures can be rewritten to reduce their complexity or at least tested further to raise the level of confidence in the code.

Chapter 3: Data Collection

I. Introduction

This chapter describes the experiment conducted to test the metric usage. Source code implemented in a system development language, Mesa, is analyzed using software metrics to verify that error-prone software can be identified. Following that, specific techniques are defined and are combined into a complete methodology for integrating maintainability into large-scale software.

The source code analyzed is part of a large-scale software project designed and implemented at a major software developer. Over 6000 procedures from a given internal release of the project code is analyzed. The software from the project is used to control the functions of a stand-alone machine. The system has characteristics of real-time software, in that it must respond almost immediately to user requirements and error conditions. Since it is a stand-alone system, it therefore contains it's own operating system used to control peripherals and environment. Finally, the system is highly computative and performance intensive.

For a complete understanding of what the data analysis indicates, it is important to realize the nature of the Mesa language, the various levels at which the data was obtained, and the tool which calculates the metric values.

II. Mesa

Mesa is a strongly-typed language with full system capabilities. As such, it is immensely detailed and functionally general. It supports full

concurrency and contains, as part of the language itself, operating system synchronization capabilities such as monitors and semaphores. It also provides full signal processing capabilities. Many programmers familiar with Mesa compare its inherent complexity and functionality with that of the Ada programming language.

Mesa is fully modularized from the procedure level on up. Using Mes terminology, multiple procedures make up a file, and multiple files make up a module. Note that the use of the term module here is synonymous with a sub-system. Further discussion of the breakdown of the various levels of Mesa source code is presented in the following section.

The inherent complexity of a programming language is dependent on the person doing the assessment. If a programmer is very familiar with a language, he might subjectively calculate a level of complexity for a particular piece of source code much lower than someone who is not as familiar with particular constructs. However, Mesa has several functionally general constructs worthy of note.

For example, the order of parameter usage in procedure calls is completely arbitrary. By specifying the formal parameter names with the argument, the parameters may be presented to the procedure in any order. If the formal parameters are not specified, the order is assumed to be that of the procedure definition. The formal parameter names are separated from the arguments by a colon in the procedure call.

Similarly, in a procedure definition itself, default values may be presented to any particular parameters. A left arrow following the parameter designates a default value, which could be a constant or a complete expression. Any parameters with defaults can be omitted from a procedure call. If the arguments are presented, they take the value of the argument; if not, they take the value of the default. Procedures themselves are data types which can

be passed as objects. An example of parameter ordering and defaults is given in Figure 4.

Also in Mesa, the programmer is completely responsible for memory allocation of all data space required, except for the base data types. Space is allocated from and returned to system or user-defined "heaps." Descriptors (masks) and user-defined sequences can be used to provide dynamic array data structures.

Signals and error data types, also inherent in the language definition, are used in a variety of ways in Mesa. Signals must be caught and properly handled using ENABLE statements or "catch phrases" in argument lists.

Mesa is a language fully capable of real-time, concurrent system development. Users of Mesa agree that it's inherent complexity exceeds the complexity of most programming languages existing today. This type of detailed language provides interesting challenges to metric analysis.

III. Levels of Data

A large amount of data was collected for this research, including the code metrics, the data from which the structure and hybrid metrics were calculated, and the error data. These various types of data were collected at different levels of granularity.

The development environment refers to three levels of abstraction in their developing systems. The lowest is the *procedure* level, as defined by a procedure of source code in the Mesa language. The second level of abstraction is a *file*, consisting of several procedures. Multiple files combine

```
DECLARATION:


SomeProc:  PROCEDURE [ i:   INTEGER, j: CARDINAL <- 1, k:   BOOLEAN ]
                     RETURNS [ x, y:   INTEGER ] =
        BEGIN
        ●
        ●
        ●
        END;




USE:


 [ q, p ]  <-  SomeProc [ k:   FALSE, i: 23 ];
```

Figure 4. **An example of parameter ordering and defaults in Mesa.**

to form the core of the third level of granularity, the *module*, which is a complete sub-system with a high degree of functionality.

Initially, it was hoped that all of the data could be obtained at the procedure level. That is, for each procedure analyzed, calculate all the metrics and determine the number of errors resulting from a logical mistake existing in that procedure. For various reasons this was not possible.

The code metrics are generated at the procedure level. Due to restraints on time and facilities, the structure data was only available at the file level. That is, data which defines the communications among components of the code was only obtained among individual files, and the structure and hybrid metrics were calculated on that level. Further discussion of how the structure data was collected and used is presented in the next section.

To obtain the structure metrics at higher levels, simple linear sums were used. The only problem this caused was with the Information Flow metric, which normally has values in the hundreds of thousands at the procedure level. Therefore, summing the values created overflow problems. This is solved by taking the log base 10 of the Information Flow metric values to obtain manageable numbers [CANJ85].

The error database was consistently kept at the module level, indicating only that an error occurred in a particular module. An error is defined to be a deviation from the expected output of a particular test case, or an incidental observation of incorrect action on the part of the operating code. The code analyzed was taken from a specific internal release, therefore the errors described are true defects and not indications of the need for additional functional enhancement.

Other pieces of information are stored with the error database entry, such as text descriptions of the problem, the person responsible, etc., but nothing else of interest to this study. Often individual files were noted as the possible source of the error, but this did not occur with enough consistency to be statistically relevant.

Having the data at various levels does not impede the formulation of a methodology in which metrics are used, but it is important to understand at what level each result or discussion is based.

IV.   The Metrics Collection Tool

As stated before, no metric was considered for use in this research which was not automatable. When dealing with large-scale software projects, it is infeasible to address any aspect of the code manually. Therefore, a tool to perform the analysis on the code and calculate the metrics value was constructed.

The analyzer is actually sectioned into two pieces, one to generate the code metrics and a statistical report, and the second to generate the data from which the structure metrics are calculated. The metric analyzer is shown in Figure 5.

The code metric analyzer statically evaluates each component of syntactically correct source code and generates the metrics for each procedure. At any point, a statistical report can be generated which gives a breakdown by the LOC, Effort, and Cyclomatic Complexity code metrics, calculating means, standard deviations, minimums and maximums. Also, based on a parameter to the tool, the report identifies the procedures which have the highest metric values considering the top N percent of the total source

Figure 5. The Metric Analyzer Tool.

analyzed. Furthermore, from that highest N percent, the report indicates which procedures overlapped all three code metrics, or any combination of two.

This overlap report provides an immediate indicator of where potentially serious problems exist. Using threshold values with varying degrees of seriousness, the highest violators of metric tolerances can be identified and investigated. A detailed discussion of a flag / alarm system which formalizes this concept is presented in Chapter 4.

An example of the statistical report run on the code for the code metric analyzer itself is given in Appendix C. The User's Guide and Implementation Guide for the code metric analyzer is given in Appendices D and E.

The data used to calculate the structure and hybrid metrics is obtained from the output of an existing tool in the development environment called the Include Checker. This tool is used to inform a system developer of the proper order in which to rebuild the components of a system, based on the use of specific files by other files. The important aspect of the output for this research is that it identifies communication lines between files of a module (subsystem).

Basically, the Include Checker associates all files which communicate with a given file. The structure data took the form of simple lists: each file has associated with it a list of other files that it "uses" in some way. The use could be called procedures, shared data references, declarations, or a combination of these.

The Cluster structure metric fits well into this scheme. In fact, its definition lends itself to analysis at this level. However, because of the level of

data available, it is actually a modified Information Flow metric that is used in this research.

The fan_in and fan_out values of the modified information flow metric are the same as those defined originally except for one detail. The deviation is that the calculation of fan_in and fan_out is an overkill count based on total communication lines, since the structure data does not distinguish between flows into and out of a file. The original definition of the metric is also an overkill of communication lines in that all procedures which reference a global data structure communicate with each other. The definition used in this study also assumes that all communication is two-way. This deviation, while not strictly as the original definition specified, still yields important aspects of the source code in terms of complexity.

V.   Conclusion

This research is based on the development of a large system implemented in Mesa. To generalize analysis techniques and to make accurate conclusions from that analysis, a full understanding is needed of the type of language analyzed and of the levels of abstraction for the data collection.

In Chapter 4 the complete data analysis used to validate the study and derive further analysis tools is described.

Chapter 4:   Data Analysis

I.   Introduction

       With the tool in place and the data gathered, analysis was performed to
verify that the metrics were performing in the manner intended.
Specifically, it is important to access how well the metrics indicated the error-
prone software and establish a scale of "acceptable" metric values.   Also, using
regression analysis, predictor equations are developed to assist in the
usefulness of the tool.   Each of these areas of analysis and the results are
described below.

II.   Intermetric and Error Correlations

       Correlations among the various metrics and between the metrics and
the error data are essential to gain an understanding of how useful the metrics
are at indicating danger areas and determining which metrics focus on
similar attributes.

       The correlation matrix for the code metrics is displayed in Figure 6.   LOC
refers to Lines of Code, N, V and EFF are Halstead's length, volume and effort, CC
is McCabe's Cyclomatic Complexity, and ERR represents the number of errors.

       Because of the nature of the error data, the correlations are performed
at the module level.   Note that all of the code metrics correlated very high
(values ranging from 0.852 to 0.998) with each other.   This verifies previous
study's results and indicates that the code metrics all tend to measure similar
aspects of the code, namely the internal complexity [HENS81b] [CANJ85]
[HENS88b].

	LOC	N	V	EFF	CC	ERR
LOC	1.00					
N	0.987	1.00				
V	0.982	0.998	1.00			
EFF	0.852	0.884	0.908	1.00		
CC	0.989	0.998	0.993	0.861	1.00	
ERR	0.837	0.831	0.843	0.828	0.814	1.00

Figure 6.   Intermetric and Error Correlations for Code Metrics.

The correlations between code metrics and defect occurrences (errors) is also significantly high (0.814 through 0.843). This indicates that the code metrics do successfully establish where the errors exist in the source code. The fact that no one metric shows a substantially higher correlation to errors than the others indicates that a single given metric cannot be used as "the" metric for the Mesa language or the development environment.

Figure 7 shows the correlations among two code metrics (LOC and V) and the structure and hybrid metrics. WOOD represents Woodfield's Review Complexity, CLUS is Belady's Cluster metric, INFO represents Henry and Kafura's Information Flow metric, and ERR again represents the number of errors.

Error data is once again correlated to all the metrics. Note that the information flow metric does not correlate well with the code metrics. Again, this verifies past studies and indicates that the information flow structure metric and code metrics are examining different aspects of software complexity.

The Woodfield hybrid metric correlated well with the code metrics. This is due to the fact that the hybrid metric is, by definition, affected greatly by Halstead's effort code metric. Belady's cluster metric also correlated fairly high to both the code metrics and the other structure metrics. Since this is not technically a hybrid metric and not inherently affected by code metrics, this would indicate that the cluster metric addresses aspects of both types of complexity.

The correlations to errors are considerably higher for the structure and hybrid metrics than for the code metrics. This indicates that the structure data yields a higher understanding of error-prone complexity in this environment.

	LOC	V	WOOD	CLUS	INFO	ERR
LOC	1.00					
V	0.982	1.00				
WOOD	0.925	0.901	1.00			
CLUS	0.925	0.891	0.999	1.00		
INFO	0.775	0.775	0.930	0.925	1.00	
ERR	0.837	0.843	0.936	0.919	0.884	1.00

Figure 7.   Intermetric and Error Correlations including
Structure and Hybrid Metrics.

III.   Threshold Determination

Any use of software metrics must be accompanied by an understanding of what the metrics are attempting to indicate about complexity and therefore what appropriate values for the metrics should be. Since this study is dealing with large-scale software, individual tolerances at the procedure level can only be intuitively estimated. For higher levels, these values can easily be scaled depending on the situation.

Tolerances for Lines of Code, Halstead's Effort, and McCabe's Cyclomatic Complexity are given in Figure 8. Two levels of concern are defined, one at which you merely raise a flag and the second at which an alarm is sounded. Combinations of flags and alarms across the metrics indicate what action should be taken.

Taken individually, a flag indicates that the additional complexity should be verified to be manageable and/or justified. However, there can be little justification for a procedure whose metric's values sound an alarm.

The previous paragraphs require qualification. If a procedure raises a single flag and no alarms, this is certainly not where effort should be concentrated. Even a single alarm can be deceptive. For example, a straightforward output procedure with many display lines would make the Lines of Code metric sound an alarm, but the Effort and Cyclomatic Complexity would indicate that there is no problem. Conversely, a procedure which processes a huge Select (Case) statement would sound a Cyclomatic Complexity alarm, but not raise concern in the others.

Therefore, the metrics values must be considered in conjunction. Rules of thumb might include investigating a particular procedure individually when it raises three flags, two flags and an alarm, or two or more alarms.

	"Safe" Zone	Flag	Alarm
LOC	Under 50	50 - 100	Over 100
Effort	Under 50000	50000 - 100000	Over 100000
CC	Under 10	11 - 20	Over 20

Figure 8. Tolerances for code metrics at the procedure level.

Figures 9, 10, and 11 show the percentage of procedures from 10 modules which fall into various distributions according to Lines of Code, Halstead's Effort, and McCabe's Cyclomatic Complexity, respectively.

Note that the metric values which are not large enough to raise a flag are classified as "safe." This does not mean, of course, that a procedure with only 20 lines of code will not contain an error. It does mean, however, that the procedure is less likely to contain an error, and even if it does contain an error, the low level of complexity allows the error to be found quickly and be addressed with less difficulty.

IV.   Predictor Equations

Analysis was performed to give the user of the metric tool an additional indicator of software maintainability. Regression analysis was performed with the number of errors as the dependent variable and various metric values as the independent variables. This yields equations which predict the number of errors that can be expected in a module of source code.

The "best" equations are established by evaluating their R-squared values and by examining their relative rankings using the MSE and C(p) statistics. The R-squared value of a given regression equation is an estimate of the percentage of data that is explained by that equation.

The MSE statistic is calculated by summing the squares of the difference between the actual and the predicted values. This is performed for all observations and the mean calculated. The lower the MSE value, the better the predictor equation. MSE measures the "noise" in the model, i.e. determines the unexplained variability in the model.

Module	1-30	31-50	51-100	101-200	> 200
1	97	2	1	0	0
2	91	6	2	1	0
3	94	4	2	0	0
4	90	5	4	1	0
5	94	5	1	0	0
6	93	4	2	0	1
7	85	9	4	1	1
8	94	5	1	0	0
9	94	2	2	1	1
10	93	3	2	1	1

● FLAG   ● ALARM

Figure 9.   Percentage Distribution of Lines of Code.

Module	10000	50000	100000	200000	> 200000
1	83	13	2	1	1
2	62	28	6	2	2
3	74	17	4	2	3
4	57	27	7	5	4
5	57	29	9	3	2
6	69	20	5	3	3
7	50	25	8	7	10
8	62	27	5	3	3
9	74	21	3	1	1
10	66	19	8	4	3

● FLAG   ● ALARM

Figure 10.   Percentage Distribution of Halstead's Effort.

Module	1 - 2	3 - 10	11 - 20	21 - 50	> 50
1	74	21	4	1	0
2	50	37	6	6	1
3	52	37	7	3	1
4	47	42	8	3	0
5	48	43	5	4	0
6	52	36	8	3	1
7	37	43	12	6	2
8	47	42	8	2	1
9	65	21	8	5	1
10	58	30	7	3	2

● FLAG   ● ALARM

Figure 11.   Percentage Distribution of McCabe's Cyclomatic Complexity.

The C(p) measurement is a compromise statistic between bias and simplicity. If too many parameters are used in a given model, the C(p) value increases. Likewise, if too few independent variables are used, the bias towards those few is large and the C(p) value increases. The C(p) statistic is measured by summing the variance over the total number of observations. This sum should be equal to the number of variables in the model.

Not all metrics need to be considered to establish a valid predictor equation, and many combinations are examined. From these, five equations are recommended, based on the R-squared values, and the MSE and C(p) statistics. These equations are given in Figure 12. The R-squared values for these equations range from 0.89 to 0.99. The complete set of equations considered with their statistical relevance is given in Appendix F.

Figure 13 shows the predicted number of errors for 10 modules using the first regression equation from Figure 12. This equation uses the metric values from Woodfield's Review Complexity, Belady's Cluster metric, Henry and Kafura's Information Flow, Halstead's Volume, and Lines of Code. This equation was chosen because of its high R-squared (0.99) value.

Note that what the equation is actually predicting is the number of errors that will be found given the same amount and concentration of testing that was performed on the data which was used to generate the predictor equations.

The level of the data used to generate these predictor equations is important. Since error data was only available at the module level, the regression analysis had to be performed at that level. Therefore, the equations presented in Figure 12 are only valid at the module level.

```
Err = 2.899E-07  WOOD  -  8.188E-04  CLUS  -  1.868E-04  V  +
      1.425E-02  LOC  +  2.990  INFO

Err = 5.001E-05  CLUS  +  8.161E-05  V  -  4.294E-03  LOC

Err = 8.827E-07  EFFORT  +  1.530E-03  N  +  9.505E-03  LOC  -
      5.004E-02  CC  -  5.986E-05  V

Err = 9.508E-03  LOC  +  6.872E-07  EFFORT  -  4.907E-02  CC  +
      1.188E-03  N

Err = 1.706E-04  V  -  4.679E-02  CC  +  9.360E-03  LOC  +
      2.662E-04  N
```

Figure 12.   Regression equations to predict the number of errors per module.

Actual Errors	Predicted Errors
34	29.181
31	31.574
147	147.000
27	25.496
53	54.005
0	-0.850
12	17.714

Figure 13.   Actual vs Predicted errors using the first predictor equation.

The fact that these predictor equations are valid only at the module level restricts their use, but the technique to generate them is completely general. Therefore, additional regression equations can be easily calculated for lower (file and procedure) levels if the error data is collected at those levels.

V.   Conclusion

The analysis of the internal release shows that the metrics are identifying error-prone software and that further refinement and concentrated testing can reduce the maintenance tasks required. The threshold guidelines can be used to determine violators of metrics tolerances for further analysis. The use of predictor equations can aid in the process of test case creation and takes into account the need for a view of complexity from various angles.

Now that the analysis has validated use of the metrics in the Mesa language and environment, the methodology can be formalized with unobtrusive, practical techniques which integrate maintainability into large-scale system software. The details of this methodology are presented in Chapter 5.

Chapter 5:   The Methodology

I.   Introduction

Tools are created, metrics established, data validated, and techniques defined.   How then does all this combine into a unified whole?   A major goal of this study is to define a complete methodology for integrating maintainability into large-scale software.

A methodology can be defined as a set of procedures and tools which, when used correctly, will formulate a process designed to meet specific objectives.   The process in this research is large-scale software development and the objective is to develop that software so that it is maintainable.

An interesting concern came quickly to light as this research began. That was the realization that established companies which design and implement large-scale software products are reluctant to make major changes in their software development process.   Often times, immediate deadlines and budget restrictions obscure long-term advantages, even when the techniques presented are proven to enhance productivity.

Maintenance is an expensive portion of the software life cycle, but it is still viewed by many software developers to be a post-production problem. Managment would certainly prefer that any effort to increase the quality of their software do so with little disruption to the current development process. Therefore, another important objective of this methodology is that it be as unobtrusive as possible.

To define such a methodology, it is helpful to examine a fundamental software development technique called iterative enhancement and how it relates to current industry practices.

II. Iterative Enhancement

The concept of iterative enhancement, as defined by Basili, describes a development scheme which inherently supports complexity analysis at the implementation stage [BASV75]. Iterative enhancement is a practical approach to the creation of new software systems. In it, a bare skeleton of the system is fully implemented, then that skeleton is augmented by a particular feature. After that feature is fully tested, the next feature is added, and so on.

Each iteration consists of designing the implementation of a selected task, coding and debugging that task, and analyzing the existing partial implementation at that stage. The analysis also defines what tasks should be added to the project list, in addition to the features of the final project which have yet to be implemented. Note that the idea of iterative enhancement as used here is different from other techniques which implement an almost complete system, then iteratively refine and reorganize until an acceptable design and implementation is achieved.

This technique is rarely used in its purest form. However, a common approach in industry borders on this concept. In the process of creating a new software system, many companies set deadlines for specific internal releases of the software. They also predict a final launch date for the first shipment to the customer. These deadlines might be manipulated as unforeseen problems arise, or the release dates can be held firm and justifications given for any feature not appearing in a particular release that was originally scheduled.

Each internal release is designed with particular goals in mind, which allows software management to assess the progress of the development. Between releases, individual programmers test their code, and when a collection of related modules are ready, integration tests are performed on larger sections of the code. The designated release points allow complete system tests to be performed.

The fundamental differences between Basili's iterative enhancement concept and industry practices is that in large-scale development, multiple features are developed at each stage, and error correction goes hand-in-hand with new development. However, these release points roughly correspond to the full system analysis stage in the iterative enhancement technique. Therefore, they also provide opportunities to measure the complexity of the system at intermediate points in its development, and determine where complexity problems are being created.

Figure 14 illustrates the integrated concepts of internal releases and complexity analysis in the waterfall model. The risk analysis stages in Boehm's spiral model can also be viewed as appropriate points for metric analysis integration.

III. Granularity

In large-scale system development, the use of the modified iterative enhancement concept can also be brought down to lower levels in the development structure. Unit managers define similar task lists for the work necessary for their section of the system. Before a system release point occurs, the smaller subsystems are frozen so that unit testing can be performed to establish confidence in the code which falls under these individual umbrellas.

Figure 14. Large-scale development process with release points and metric analysis.

Each of these points are appropriate places for metric analysis to occur. Errors found at this level are more easily fixed since the scope of where the problem originates is smaller and better understood. Metric evaluation can indicate where that important testing should be concentrated and where error-prone code exists.

Even individual programmers can work on their code with this technique. Once a programmer determines that the code he is responsible for is fully implemented, metric evaluation can pinpoint exact procedures which will probably, if not immediately, cause problems. This identified code can be rewritten or at the very least thoroughly tested. The individual tests run by programmers can uncover many problems that might not show up until further in the testing hierarchy under regular circumstances. Programmers are highly motivated to find any problems in their code before it advances to higher levels of testing and someone else informs them they have a problem.

Complexity analysis can therefore be integrated into extremely early points of the development and testing process. And as stated in Chapter 1, the earlier an error is uncovered and fixed, the less costly the change.

IV. The Process

Now we can observe the software development process with the metrics evaluation fully integrated into all stages.

Once the functionality of an individual internal release point is defined, the system designed, and the functionality decomposed to unit and programmer levels, the implementation process begins. The methodology proposed here is based at the implementation and testing levels since this causes the least disruption to the existing development process.

Individual programmers begin implementing their relatively small portion of the logic for the overall system. Once they establish a functional subset of their code, they use the metric analysis tool to generate metric values and a statistical evaluation of their code based on the metrics. This gives immediate feedback as to the volatile portions of their code. Threshold values can be used to section off those procedures which raise flags and alarms as the situation dictates. If predictor equations are available at that level, these can indicate the number of errors that can be expected as well.

Based on their analysis, portions of their code can be rewritten to reduce the complexity levels. This rewriting process itself is highly likely to uncover logical errors in previously complex procedures. If rewriting is not considered necessary or feasible, the programmer's testing efforts can at least be concentrated on the potentially dangerous code.

Once the programmers have established their portions of the system, pieces are brought together for unit tests. At this stage, the analysis can be run on the larger subset of the overall system. Again, the metric analysis can identify areas that are potentially dangerous, this time from a slightly more global viewpoint. Structure metrics tend to become more important at this stage since there is more cohesive communication among the larger components of the code. Using predictor equations at this level can be very informative.

After unit testing, a full internal release is established. Metric analysis at this stage can give an even more global view of the developing system. Errors concerning integration problems and higher level communication are likely to be uncovered here.

Once the system internal release is tested, new tasks to fix errors and increase the growing functionality of the developing system are defined.

Progress toward the next internal release is begun and the cycle repeats itself. Eventually, the last internal release is performed with little or no problems detected, and the product is scheduled for an external release.

V. Integration

This methodology was presented to a commercial software development environment with encouraging results. Plans were made to distribute the metrics tool to various levels of the developing system process, including the individual programmers.

An important caution must be made concerning the use of the metric tool. Any evaluatory technique such as the one described in this research concludes with the result that something is good or bad. It must be made clear to the software writers that the tool is used only as a way to evaluate code and not to judge the productivity or usefulness of individuals. If software developers fear the tool, the entire concept of metric evaluation will be undermined.

If the methodology described in this chapter is used as intended, to help guide testing processes and identify error-prone software, the end result will be a software product that is more reliable and maintainable.

VI. Conclusion

A succint review of the methodology described in this chapter will give a encapsulated understanding of the processes and tools involved. Large-scale software is developed in stages, called release points, used to assess progress and perform system tests. At these points, metric analysis is performed on the

implemented code, using specific techniques such as threshold determination and predictor equation analysis, to identify error-prone software due to high complexity. Once identified, the software can be rewritten to reduce the complexity, or at least the testing procedures are targeted toward that code. The same type of analysis is performed at the lower levels of the development process for each release, allowing the unit testers and even individual programmers the opportunity for metric analysis. Iterative progression through the release points will have a higher degree of confidence due to the metric analysis performed at each stage.

The methodology described in this chapter incorporates the various techniques and observations established by this research. Since it concentrates on integrating the use of the metric analysis without instigating another complete level to the development hierarchy, the use is practical as well as useful.

Chapter 6 describes the overall conclusions to this research and discusses future work in the area.

Chapter 6: Conclusions

I. Introduction

The results of this study are both encouraging and educational. The research as a whole was accepted well in the commercial environment it was targeted for, and definite plans are in the works for the fruits of this labor to be practically implemented.

Many conclusions gained from this research served to validate past research, while others shed important insight into the differences between real-world, large-scale software development and controlled, smaller studies.

The following section describes the particular conclusions which can be drawn from this research.

II. Conclusions of the Research

To review from Chapter 1, the goals of this research are: (1) Design and implement a metrics collection tool for the Mesa language; (2) Validate that the metrics calculated by the tool indicate error-prone software; (3) Establish regression equations which predict the number of errors which are present in the section of code; and (4) Develop a methodology using these tools and techniques which integrates maintainability into large-scale software.

The following sections address the weaknesses and strengths of the research, and specifically address the conclusions of the study.

Weaknesses

One area of this research which could be stronger is the concentration on Mesa as an individual language. There are probably several distinct constructs and abilities in Mesa which lend themselves higher code complexity. Not all of these are addressed by the metrics used in this study.

Another restriction in the usefulness of the predictor equations presented in this study is that they are only valid at the module level. This is a consequence of the data made available for the research. However, the techniques for generating the equations are general and the equations can easily be calculated for any level. Error database needs in industry is discussed further in the section on future work.

Strengths

Overall, this research can be considered a success. All major goals were achieved, and several other tangents were uncovered. Specifically, the following sum up the results of this research:

- Software quality metrics have again been shown to identify error-prone software due to a high level of complexity.

- Maintainability is a characteristic which can (and should) be integrated into software as it is produced, instead of dealing with it only as a post-production process.

- Techniques including the use of predictor equations and threshold analysis are developed to aid in the use of a metric analysis tool.

- A methodology is defined to integrate maintainability using software metrics as an evaluation scheme for guiding the testing processes already in place.

- Practical use dictates that such defined methodologies should disrupt as little of the existing development process as possible.

Overall the results are positive and motivating. The concentration on the maintenance aspect of the software development process must be continued in order to reduce the overwhelming cost of software production and service.

III. Future Work

The research presented here opens additional avenues for investigation. The methodology described uses techniques that can be modified and refined to provide even more insight into the complexity of large-scale software. These techniques, as well as new ones, can be used in the same overall environment to further the goals presented by this study.

This methodology should be integrated into another commercial environment to verify its validity and explore other techniques for identifying error-prone software. Specific emphasis should be given to the fact that it is intended to cause little disruption as possible to the existing software development system.

Important work for the future can be concentrated on the importance of industry-generated error databases, including the information they should contain and the levels at which it should be collected. These studies should consider programmer detail such as the number of lines changed to fix a bug,

the severity of the error, specific location, sections of the code affected, the time needed to find and fix the defect, etc.

The need for these must be stressed from all points of view, including the fact that a complete error history, analyzed correctly, can lead to a better understanding of where and how errors occur at a global level. This information is necessary to make the production process more complete.

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Appendix A.   Halstead Operators for Mesa

Listed on the following page are all constructs in the Mesa language that are considered operators in the calculation of Halstead's Software Science indicators. They include all reserved words and tokens which perform specific functions. Some reserved words or characters are combined as a single operator.

ABORTED	IMPORTS	PUBLIC	[ ]
ABS	IN	READONLY	..
ALL	INLINE	REAL	<- (left arrow)
AND	INT	RECORD		
ANY	INTEGER	REJECT	( )
APPLY	INTERNAL	RELATIVE	*
ARRAY	ISTYPE	REPEAT	⇒
BASE	JOIN	RESIDENT	+
BEGIN - END	LAST	RESTART	-
BOOL	LENGTH	RESUME	/
BOOLEAN	LOCKS	RETRY	~
BROADCAST	LONG	RETURN	!
CARDINAL	LOOP	RETURNS	@
CHAR	LOOPHOLE	SELECT	#
CHARACTER	MACHINE	SEQUENCE	<
CODE	MAX	SHARES	⇐
COMPUTED	MDSZONE	SIGNAL	>
CONDITION	MIN	SIZE	≽
CONTINUE	MOD	START	
DECREASING	MONITORED	STATE	
DEFINITIONS	MONITOR	STOP	
DEPENDENT	MONITORLOCK	STRING	
DESCRIPTOR	NARROW	SUCC	
DIRECTORY	NAT	THROUGH	
DO	NATURAL	TRASH	
ENABLE	NEW	TRUE	
ENDCASE	NIL	TYPE	
ENDLOOP	NOT	UNCOUNTED	
ENTRY	NOTIFY	UNSPECIFIED	
ERROR	NULL	UNTIL	
EXIT	OF	UNWIND	
EXITS	OPEN	USING	
EXPORTS	OR	VAL	
FALSE	ORD	VAR	
FINISHED	ORDERED	WAIT	
FIRST	OVERLAID	WHILE	
FOR	PACKED	WITH	
FORK	POINTER	WORD	
FRAME	PORT	ZONE	
FREE	PRED	.	
FROM	PRIVATE	{ }	
GO	PROC	;	
GOTO	PROCEDURE	=	
IF - THEN	PROCESS	,	
IF - THEN - ELSE	PROGRAM	:	

Appendix B. McCabe Constructs for Mesa

Listed below are all constructs in the Mesa language that are used as logical decision points in the calculation of McCabe's Cyclomatic Complexity.

Construct	Comment
IF	Conditional
SELECT	Multi Decision Conditional (Case)
WHILE	Loop - precondition
UNTIL	Loop - postcondition
THROUGH	Loop - elements of a set
FOR	Loop - iterative
AND	Logical AND
OR	Logical OR

Appendix C.   Statistical Report Generated by the Code Metric Analyzer

```
CODE METRICS STATISTICS
========================

Number of procedures:  149


                        LOC        CYC. COMPLEXITY        EFFORT
                      -------      ---------------       --------

        Average :     18.208           7.932            83710.710

St. Deviation :       34.506          26.430           456614.437

          Min :          1               1                39.302

          Max :        320             210            4662495.500


..............................................................................


Overlaps of highest metrics values ...

Considering the top  38 procedures (  25 percent ) ...


LOC / CC / Effort :

Total procedures =  23

  LOC      CC         EFFORT         Procedure Name
  -----   ------     --------       ----------------

    32      25        91114.359      AnalyzerImpl/RunIt
    49      28       192890.203      CMStatsImpl/Overlap
    35      16        81116.781      CMStatsImpl/QuickCC
    21       9        33310.777      CMStatsImpl/QuickEffort
    21       9        35515.578      CMStatsImpl/QuickLOC
    23      10        60963.832      CMStatsImpl/QuickName
    35       7        98389.132      CMStatsImpl/ReadMetrics
   320     210      4662495.500      Grammar/ProcessQueue
   231     151      1970947.625      Grammar/ProcessQueueCont
    23       6        37698.492      HalsteadImpl/HsCompute
    19      12        36466.429      ParserImpl/Accept
    20      10        29695.220      ParserImpl/ExistingConfiguration
    32      12        72341.656      ParserImpl/GrowTree
    70      23       220672.203      ParserImpl/Parse
    60      29       175504.125      ParserImpl/Recover
    20      10        38852.316      ParserImpl/RightScan
    22       6        51668.382      ProcMetricsImpl/PmImpress
   252     196      2424798.000      ScannerImpl/Atom
    51      35       294474.718      ScannerImpl/CollectNumber
    27      13        62963.859      ScannerImpl/ErrorContext
    29      19       127131.421      ScannerImpl/ScanFloating
    25       7        38278.285      UtilsImpl/CardToString
    33       7        75960.078      UtilsImpl/RealToString


LOC / CC :

Total procedures =   3

  LOC      CC         EFFORT         Procedure Name
  -----   ------     --------       ----------------

    24      11        19261.224      AnalyzerImpl/ProcessFile
    16       6        25507.697      ParserImpl/ActOnStack
    19       6        23037.746      ParserImpl/SyntaxError


LOC / Effort :

Total procedures =   8

  LOC      CC         EFFORT         Procedure Name
```

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   75

```
-----   ------    --------   ----------------
  34       1      27005.613  AnalyzerImpl
  22       2      31673.464  CMStatsImpl/AllocArrays
  34       2      28923.259  CMStatsImpl/MetImpress
  37       5      31019.351  CMStatsImpl/MetricStats
 141       1     240554.500  CMStatsImpl/StatsImpress
  27       1     122436.335  EncodeImpl/InitEncodeTable
  96       1     157919.593  ParserImpl
  57       1      55864.269  ScannerImpl
```

CC / Effort :

Total procedures =   4

```
  LOC     CC      EFFORT     Procedure Name
-----   ------    --------   ----------------

  15      11      27647.445  AnalyzerImpl/RunIt/BreakupFiles
  13      11      33145.804  ScannerImpl/ScanDecimal
  15      15      57725.308  ScannerImpl/ScanHex
  13      11      33145.304  ScannerImpl/ScanOctal
```

```
----------------------------------------------------------------
```

Sort by NAME :

```
  LOC     CC      EFFORT     Procedure Name
-----   ------    --------   ----------------

  34       1      27005.613  AnalyzerImpl
  11       3       5190.876  AnalyzerImpl/ClearIt
   3       3        411.194  AnalyzerImpl/ClearOutputFile
   9       1       3603.606  AnalyzerImpl/EnumerateFiles
   1       1         67.500  AnalyzerImpl/EnumerateFiles/AddEnumerating
   1       1         39.302  AnalyzerImpl/ExecutiveProc
   3       1        629.469  AnalyzerImpl/FreeNameDescriptor
  14       4       7249.634  AnalyzerImpl/GenStats
   4       3        713.118  AnalyzerImpl/GenerateStats
  17       3      13351.339  AnalyzerImpl/Initialize
   3       2        548.259  AnalyzerImpl/Initialize/Cleanup
   6       1       5941.321  AnalyzerImpl/InitializeErrors
  11       1      17862.277  AnalyzerImpl/MakeForm
   6       2       9980.321  AnalyzerImpl/MakeSWs
  24      11      19261.224  AnalyzerImpl/ProcessFile
  12       7      14610.231  AnalyzerImpl/ProcessFile/CleanUp
   3       3        431.754  AnalyzerImpl/Run
  32      25      91114.359  AnalyzerImpl/RunIt
  15      11      27647.445  AnalyzerImpl/RunIt/BreakupFiles
  14       5       3848.032  AnalyzerImpl/Unload
   1       1         71.323  AnalyzerImpl/WindowOutput
  15       1      12502.323  CMFileImpl
   4       1        951.999  CMFileImpl/ClearMetFile
   3       1        512.779  CMFileImpl/CloseMetFile
   1       1        175.663  CMFileImpl/EOFMetFile
   4       1       2143.400  CMFileImpl/GetMetRec
   4       1       1367.700  CMFileImpl/OpenMetFile
   2       1        533.290  CMFileImpl/ResetMetFile
   2       1        479.541  CMFileImpl/StoreMetRec
  27       1       5267.874  CMStatsImpl
  22       2      31673.464  CMStatsImpl/AllocArrays
   4       2       1796.011  CMStatsImpl/Cleanup
   4       1        917.552  CMStatsImpl/EncodeNewLine
   1       1        284.282  CMStatsImpl/EncodeWrite
  16       3      26407.884  CMStatsImpl/MakeNewNode
  34       2      28923.259  CMStatsImpl/MetImpress
   4       1        917.552  CMStatsImpl/MetNewLine
   1       1        284.282  CMStatsImpl/MetWrite
  37       5      31019.351  CMStatsImpl/MetricStats
   8       2       1833.941  CMStatsImpl/OutEncodeMap
  29       3      25808.105  CMStatsImpl/OutSort
  49      28     192890.203  CMStatsImpl/Overlap
  35      16      81116.781  CMStatsImpl/QuickCC
```

21	9	33310.777	CMStatsImpl/QuickEffort
21	9	35515.578	CMStatsImpl/QuickLOC
23	10	60963.832	CMStatsImpl/QuickName
35	7	98389.132	CMStatsimpl/ReadMetrics
141	1	240554.500	CMStatsImpl/StatsImpress
4	1	917.552	CMStatsImpl/StatsNewLine
1	1	284.282	CMStatsImpl/StatsWrite
8	1	1589.004	EncodeImpl
11	5	21177.693	EncodeImpl/DecodeChar
15	3	20339.093	EncodeImpl/DecodeId
9	5	16213.844	EncodeImpl/EncodeChar
14	3	26582.455	EncodeImpl/EncodeId
27	1	122436.335	EncodeImpl/InitEncodeTable
10	1	1821.996	Grammar
4	1	1089.273	Grammar/AssignDescriptors
7	1	382.378	Grammar/Initialize
320	210	4662495.500	Grammar/ProcessQueue
231	151	1970947.625	Grammar/ProcessQueueCont
5	1	427.400	HalsteadImpl
23	6	37898.492	HalsteadImpl/HsCompute
13	3	10600.215	HalsteadImpl/HsCompute/HsFree
11	3	19002.236	HalsteadImpl/HsDump
5	1	1913.293	HalsteadImpl/HsInit
15	4	16419.607	HalsteadImpl/HsOperand
15	4	16419.607	HalsteadImpl/HsOperator
4	1	313.684	McCabeImpl
5	2	3094.849	McCabeImpl/McCompute
11	1	59653.515	McCabeImpl/McDump
1	1	802.894	McCabeImpl/McIncrement
13	1	9262.550	McCabeImpl/McInit
96	1	157919.593	ParserImpl
19	12	36466.429	ParserImpl/Accept
15	6	25507.597	ParserImpl/ActOnStack
10	7	11233.350	ParserImpl/AddLeaf
1	1	217.944	ParserImpl/Advance
4	2	4598.145	ParserImpl/Allocate
9	7	10718.255	ParserImpl/CheckTree
3	2	742.585	ParserImpl/Discard
12	2	5194.714	ParserImpl/DisplayNode
1	2	233.022	ParserImpl/EraseQueue
2	2	738.402	ParserImpl/EraseStack
20	10	29695.220	ParserImpl/ExistingConfiguration
6	3	8325.503	ParserImpl/ExpandQueue
12	3	17530.996	ParserImpl/ExpandStack
7	5	6001.291	ParserImpl/FindNode
2	3	2090.743	ParserImpl/FreeRowList
2	4	4213.928	ParserImpl/GetNTEntry
32	12	72341.656	ParserImpl/GrowTree
1	1	67.500	ParserImpl/InputLoc
2	1	1608.906	ParserImpl/LinkHash
1	1	119.589	ParserImpl/NewLine
6	6	7728.919	ParserImpl/NextRow
70	23	220672.203	ParserImpl/Parse
14	1	8044.816	ParserImpl/ParseInit
2	1	145.296	ParserImpl/ParseReset
14	8	22408.482	ParserImpl/ParseStep
1	1	95.097	ParserImpl/ParserID
60	29	175504.125	ParserImpl/Recover
4	4	5148.029	ParserImpl/RecoverInput
20	10	38852.318	ParserImpl/RightScan
19	6	23037.746	ParserImpl/SyntaxError
3	3	8990.468	ParserImpl/TypeSym
3	2	742.585	ParserImpl/UnDiscard
4	1	713.656	ParserImpl/input
11	1	1465.634	ProcMetricsImpl
5	1	4319.817	ProcMetricsImpl/PmDump
7	2	9743.224	ProcMetricsImpl/PmGetProcName
22	6	51668.382	ProcMetricsImpl/PmImpress
1	1	553.801	ProcMetricsImpl/PmLines
1	1	528.000	ProcMetricsImpl/PmMcCabe
1	1	632.279	ProcMetricsImpl/PmOperand
1	1	632.279	ProcMetricsImpl/PmOperator
4	1	1681.699	ProcMetricsImpl/PmPop
4	1	2049.399	ProcMetricsImpl/PmPush
7	1	3482.928	ProcMetricsImpl/PmPush/PmInit
57	1	55864.269	ScannerImpl

5	3	7494.709	ScannerImpl/AppendDecimal
4	2	7202.639	ScannerImpl/AppendHex
4	1	4383.412	ScannerImpl/AppendOctal
5	3	6696.540	ScannerImpl/AppendToScale
252	196	2424798.000	ScannerImpl/Atom
51	35	294474.718	ScannerImpl/CollectNumber
3	2	1391.486	ScannerImpl/CollectNumber/Accept
2	1	1808.729	ScannerImpl/EnterLit
27	13	62963.859	ScannerImpl/ErrorContext
3	3	1787.488	ScannerImpl/Escape
7	2	6539.538	ScannerImpl/ExpandBuffer
7	4	3765.871	ScannerImpl/FillBuffer
1	1	553.801	ScannerImpl/ItemHandleToStreamIndex
1	2	462.857	ScannerImpl/NextChar
11	4	8423.299	ScannerImpl/ResetScanIndex
13	11	33145.804	ScannerImpl/ScanDecimal
4	7	3586.635	ScannerImpl/ScanError
29	19	127131.421	ScannerImpl/ScanFloating
15	15	57726.308	ScannerImpl/ScanHex
21	2	10766.739	ScannerImpl/ScanInit
13	11	33145.804	ScannerImpl/ScanOctal
11	8	25329.830	ScannerImpl/ScanOctalChar
3	2	619.347	ScannerImpl/ScanReset
1	1	119.539	ScannerImpl/ScanStats
2	3	3270.918	ScannerImpl/ValidFraction
4	1	326.231	UtilsImpl
25	7	38278.295	UtilsImpl/CardToString
33	7	75960.078	UtilsImpl/RealToString
2	1	1162.287	UtilsImpl/StringEqual
2	1	1306.190	UtilsImpl/StringLess

Sort by LOC :

LOC	CC	EFFORT	Procedure Name
320	210	4662495.500	Grammar/ProcessQueue
252	196	2424798.000	ScannerImpl/Atom
231	151	1970947.625	Grammar/ProcessQueueCont
141	1	240554.500	CMStatsImpl/StatsImpress
96	1	157919.593	ParserImpl
70	23	220672.203	ParserImpl/Parse
60	29	175504.125	ParserImpl/Recover
57	1	55864.269	ScannerImpl
51	35	294474.718	ScannerImpl/CollectNumber
49	28	192890.203	CMStatsImpl/Overlap
37	5	31019.351	CMStatsImpl/MetricStats
35	7	98389.132	CMStatsImpl/ReadMetrics
35	16	81116.781	CMStatsImpl/QuickCC
34	1	27005.613	AnalyzerImpl
34	2	28923.259	CMStatsImpl/MetImpress
33	7	75960.078	UtilsImpl/RealToString
32	12	72341.656	ParserImpl/GrowTree
32	25	91114.359	AnalyzerImpl/RunIt
29	19	127131.421	ScannerImpl/ScanFloating
29	3	25808.105	CMStatsImpl/OutSort
27	13	62963.859	ScannerImpl/ErrorContext
27	1	5267.874	CMStatsImpl
27	1	122436.335	EncodeImpl/InitEncodeTable
25	7	38278.285	UtilsImpl/CardToString
24	11	19261.224	AnalyzerImpl/ProcessFile
23	10	60963.832	CMStatsImpl/QuickName
23	6	37698.492	HalsteadImpl/HsCompute
22	2	31673.464	CMStatsImpl/AllocArrays
22	6	51668.382	ProcMetricsImpl/PmImpress
21	9	25515.578	CMStatsImpl/QuickLOC
21	2	10766.739	ScannerImpl/ScanInit
21	9	33310.777	CMStatsImpl/QuickEffort
20	10	29695.220	ParserImpl/ExistingConfiguration
20	10	38852.316	ParserImpl/RightScan
19	12	36466.429	ParserImpl/Accept
19	6	23037.746	ParserImpl/SyntaxError
17	3	13351.339	AnalyzerImpl/Initialize
16	6	25507.697	ParserImpl/ActOnStack
16	3	26407.884	CMStatsImpl/MakeNewNode

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   78

```
15    1    12502.323   CMFileImpl
15   15    57726.308   ScannerImpl/ScanHex
15    3    20339.093   EncodeImpl/DecodeId
15   11    27647.445   AnalyzerImpl/RunIt/BreakupFiles
15    4    16419.607   HalsteadImpl/HsOperand
15    4    16419.607   HalsteadImpl/HsOperator
14    5     3843.032   AnalyzerImpl/Unload
14    3    26502.455   EncodeImpl/EncodeId
14    8    22408.482   ParserImpl/ParseStep
14    4     7249.534   AnalyzerImpl/GenStats
14    1     8044.816   ParserImpl/ParseInit
13   11    33145.804   ScannerImpl/ScanDecimal
13   11    33145.804   ScannerImpl/ScanOctal
13    3    10600.215   HalsteadImpl/HsCompute/HsFree
13    1     9262.550   McCabeImpl/McInit
12    3    17530.996   ParserImpl/ExpandStack
12    2     5194.714   ParserImpl/DisplayNode
12    7    14610.231   AnalyzerImpl/ProcessFile/CleanUp
11    3     5190.876   AnalyzerImpl/ClearIt
11    3    19002.236   HalsteadImpl/HsDump
11    4     8423.299   ScannerImpl/ResetScanIndex
11    5    21177.593   EncodeImpl/DecodeChar
11    1     1485.834   ProcMetricsImpl
11    1    59552.515   McCabeImpl/McDump
11    8    25323.830   ScannerImpl/ScanOctalChar
11    1    17852.277   AnalyzerImpl/MakeForm
10    1     1821.996   Grammar
10    7    11233.350   ParserImpl/AddLeaf
 9    7    10718.255   ParserImpl/CheckTree
 9    1     3603.606   AnalyzerImpl/EnumerateFiles
 9    5    16213.844   EncodeImpl/EncodeChar
 8    2     1833.941   CMStatsImpl/OutEncodeMap
 8    1     1589.004   EncodeImpl
 7    1     3482.928   ProcMetricsImpl/PmPush/PmInit
 7    1      382.378   Grammar/Initialize
 7    5     6001.291   ParserImpl/FindNode
 7    2     9743.224   ProcMetricsImpl/PmGetProcName
 7    4     3765.871   ScannerImpl/FillBuffer
 7    2     6539.538   ScannerImpl/ExpandBuffer
 6    3     8325.503   ParserImpl/ExpandQueue
 6    2     9980.321   AnalyzerImpl/MakeSWs
 6    1     5941.321   AnalyzerImpl/InitializeErrors
 6    6     7728.919   ParserImpl/NextRow
 5    1      427.400   HalsteadImpl
 5    3     6696.540   ScannerImpl/AppendToScale
 5    1     4319.817   ProcMetricsImpl/PmDump
 5    3     7494.709   ScannerImpl/AppendDecimal
 5    2     3094.849   McCabeImpl/McCompute
 5    1     1913.293   HalsteadImpl/HsInit
 4    1      326.231   UtilsImpl
 4    1      313.684   McCabeImpl
 4    1      713.656   ParserImpl/input
 4    2     7202.639   ScannerImpl/AppendHex
 4    1     1089.273   Grammar/AssignDescriptors
 4    1     2049.399   ProcMetricsImpl/PmPush
 4    1     1367.700   CMFileImpl/OpenMetFile
 4    1     1681.699   ProcMetricsImpl/PmPop
 4    1     4383.412   ScannerImpl/AppendOctal
 4    2     4598.145   ParserImpl/Allocate
 4    1     2143.400   CMFileImpl/GetMetRec
 4    1      951.999   CMFileImpl/ClearMetFile
 4    3      713.118   AnalyzerImpl/GenerateStats
 4    2     1796.011   CMStatsImpl/Cleanup
 4    1      917.552   CMStatsImpl/StatsNewLine
 4    1      917.552   CMStatsImpl/MetNewLine
 4    4     5148.029   ParserImpl/RecoverInput
 4    7     3586.625   ScannerImpl/ScanError
 4    1      917.552   CMStatsImpl/EncodeNewLine
 3    2      742.585   ParserImpl/UnDiscard
 3    3      411.194   AnalyzerImpl/ClearOutputFile
 3    2      548.259   AnalyzerImpl/Initialize/Cleanup
 3    2      742.585   ParserImpl/Discard
 3    3      431.754   AnalyzerImpl/Run
 3    3     8990.468   ParserImpl/TypeSym
 3    2      619.347   ScannerImpl/ScanReset
 3    3     1787.488   ScannerImpl/Escape
```

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   79

3	1	512.779	CMFileImpl/CloseMetFile
3	1	629.469	AnalyzerImpl/FreeNameDescriptor
3	2	1391.486	ScannerImpl/CollectNumber/Accept
3	3	3273.918	ScannerImpl/ValidFraction
2	1	1808.729	ScannerImpl/EnterLit
2	3	2090.743	ParserImpl/FreeRowList
2	4	4213.928	ParserImpl/GetNTEntry
2	1	1602.906	ParserImpl/LinkHash
2	1	479.541	CMFileImpl/StoreMetRec
2	1	1152.237	UtilsImpl/StringEqual
2	1	533.290	CMFileImpl/ResetMetFile
2	1	1306.190	UtilsImpl/StringLess
2	2	738.402	ParserImpl/EraseStack
2	1	145.296	ParserImpl/ParseReset
1	1	175.663	CMFileImpl/EOFMetFile
1	2	462.857	ScannerImpl/NextChar
1	1	553.801	ProcMetricsImpl/PmLines
1	1	528.000	ProcMetricsImpl/PmMcCabe
1	1	632.279	ProcMetricsImpl/PmOperand
1	1	632.279	ProcMetricsImpl/PmOperator
1	1	67.500	AnalyzerImpl/EnumerateFiles/AddEnumerating
1	1	119.589	ParserImpl/NewLine
1	1	113.539	ScannerImpl/ScanStats
1	1	294.282	CMStatsImpl/StatsWrite
1	1	284.282	CMStatsImpl/Encodewrite
1	1	284.282	CMStatsImpl/MetWrite
1	1	553.801	ScannerImpl/ItemHandleToStreamIndex
1	1	217.944	ParserImpl/Advance
1	1	95.097	ParserImpl/ParserID
1	2	253.022	ParserImpl/EraseQueue
1	1	67.500	ParserImpl/InputLoc
1	1	802.894	McCabeImpl/McIncrement
1	1	39.302	AnalyzerImpl/ExecutiveProc
1	1	71.323	AnalyzerImpl/WindowOutput

Sort by Cyclomatic Complexity :

LOC	CC	EFFORT	Procedure Name
320	210	4662495.500	Grammar/ProcessQueue
252	196	2424798.000	ScannerImpl/Atom
231	151	1970947.625	Grammar/ProcessQueueCont
51	35	294474.718	ScannerImpl/CollectNumber
60	29	175504.125	ParserImpl/Recover
49	28	192890.203	CMStatsImpl/Overlap
32	25	91114.359	AnalyzerImpl/RunIt
70	23	220672.203	ParserImpl/Parse
29	19	127131.421	ScannerImpl/ScanFloating
35	16	81116.781	CMStatsImpl/QuickCC
15	15	57726.308	ScannerImpl/ScanHex
27	13	62963.859	ScannerImpl/ErrorContext
32	12	72341.656	ParserImpl/GrowTree
19	12	36466.429	ParserImpl/Accept
13	11	33145.804	ScannerImpl/ScanDecimal
15	11	27647.445	AnalyzerImpl/RunIt/BreakupFiles
24	11	19261.224	AnalyzerImpl/ProcessFile
13	11	33145.804	ScannerImpl/ScanOctal
23	10	60963.832	CMStatsImpl/QuickName
20	10	29695.220	ParserImpl/ExistingConfiguration
20	10	38852.316	ParserImpl/RightScan
21	9	35515.578	CMStatsImpl/QuickLOC
21	9	33310.777	CMStatsImpl/QuickEffort
14	8	22408.482	ParserImpl/ParseStep
11	8	25328.830	ScannerImpl/ScanOctalChar
9	7	10718.255	ParserImpl/CheckTree
10	7	11233.350	ParserImpl/AddLeaf
25	7	38278.285	UtilsImpl/CardToString
35	7	98389.132	CMStatsImpl/ReadMetrics
12	7	14610.231	AnalyzerImpl/ProcessFile/CleanUp
33	7	75960.078	UtilsImpl/RealToString
4	7	3586.635	ScannerImpl/ScanError
16	6	25507.697	ParserImpl/ActOnStack
22	6	51668.382	ProcMetricsImpl/PmImpress
23	6	37698.492	HalsteadImpl/HsCompute

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   80

19	6	23037.746	ParserImpl/SyntaxError
6	6	7728.919	ParserImpl/NextRow
14	5	3848.032	AnalyzerImpl/Unload
11	5	21177.693	EncodeImpl/DecodeChar
9	5	16213.844	EncodeImpl/EncodeChar
37	5	31019.351	CMStatsImpl/MetricStats
7	5	6001.291	ParserImpl/FindNode
11	4	8423.299	ScannerImpl/ResetScanIndex
7	4	3785.571	ScannerImpl/FillBuffer
15	4	16419.607	HalsteadImpl/HsOperator
15	4	16419.607	HalsteadImpl/HsOperand
2	4	4213.928	ParserImpl/GetNTEntry
14	4	7249.634	AnalyzerImpl/GenStats
4	4	5148.029	ParserImpl/RecoverInput
3	3	431.754	AnalyzerImpl/Run
4	3	713.118	AnalyzerImpl/GenerateStats
2	3	2090.743	ParserImpl/FreeRowList
5	3	6696.540	ScannerImpl/AppendToScale
2	3	3273.918	ScannerImpl/ValidFraction
5	3	7494.709	ScannerImpl/AppendDecimal
11	3	19002.236	HalsteadImpl/HsDump
13	3	10600.215	HalsteadImpl/HsCompute/HsFree
11	3	5190.976	AnalyzerImpl/ClearIt
3	3	1787.488	ScannerImpl/Escape
15	3	20339.093	EncodeImpl/DecodeId
3	3	3990.468	ParserImpl/TypeSym
14	3	25582.455	EncodeImpl/EncodeId
16	3	26407.884	CMStatsImpl/MakeNewNode
3	3	411.194	AnalyzerImpl/ClearOutputFile
17	3	13351.339	AnalyzerImpl/Initialize
11	3	17530.996	ParserImpl/ExpandStack
29	3	25808.105	CMStatsImpl/OutSort
6	3	8325.503	ParserImpl/ExpandQueue
1	2	233.022	ParserImpl/EraseQueue
2	2	738.402	ParserImpl/EraseStack
12	2	5194.714	ParserImpl/DisplayNode
4	2	4598.145	ParserImpl/Allocate
8	2	1833.941	CMStatsImpl/OutEncodeMap
34	2	28923.259	CMStatsImpl/MetImpress
4	2	1796.011	CMStatsImpl/Cleanup
3	2	548.259	AnalyzerImpl/Initialize/Cleanup
3	2	619.347	ScannerImpl/ScanReset
6	2	9980.321	AnalyzerImpl/MakeSWs
5	2	3094.849	McCabeImpl/McCompute
22	2	31673.464	CMStatsImpl/AllocArrays
21	2	10766.739	ScannerImpl/ScanInit
3	2	742.585	ParserImpl/Discard
3	2	742.585	ParserImpl/UnDiscard
4	2	7202.639	ScannerImpl/AppendHex
3	2	1391.486	ScannerImpl/CollectNumber/Accept
1	2	462.857	ScannerImpl/NextChar
7	2	6539.538	ScannerImpl/ExpandBuffer
7	2	9743.224	ProcMetricsImpl/PmGetProcName
10	1	1821.996	Grammar
5	1	1913.293	HalsteadImpl/HsInit
5	1	427.400	HalsteadImpl
7	1	382.378	Grammar/Initialize
4	1	1089.273	Grammar/AssignDescriptors
8	1	1589.004	EncodeImpl
13	1	9262.550	McCabeImpl/McInit
1	1	802.894	McCabeImpl/McIncrement
11	1	59653.515	McCabeImpl/McDump
4	1	313.684	McCabeImpl
27	1	122436.335	EncodeImpl/InitEncodeTable
27	1	5267.874	CMStatsImpl
4	1	713.656	ParserImpl/input
14	1	8044.816	ParserImpl/ParseInit
2	1	145.296	ParserImpl/ParseReset
4	1	917.552	CMStatsImpl/MetNewLine
1	1	284.282	CMStatsImpl/MetWrite
1	1	67.500	ParserImpl/InputLoc
4	1	917.552	CMStatsImpl/EncodeNewLine
1	1	284.282	CMStatsImpl/EncodeWrite
141	1	240554.500	CMStatsImpl/StatsImpress
1	1	95.097	ParserImpl/ParserID
4	1	917.552	CMStatsImpl/StatsNewLine

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   81

1	1	284.282	CMStatsImpl/StatsWrite
2	1	1608.906	ParserImpl/LinkHash
1	1	217.944	ParserImpl/Advance
1	1	119.589	ParserImpl/NewLine
96	1	157919.593	ParserImpl
1	1	832.279	ProcMetricsImpl/PmOperator
1	1	832.279	ProcMetricsImpl/PmOperand
1	1	528.300	ProcMetricsImpl/PmMcCabe
1	1	553.801	ProcMetricsImpl/PmLines
15	1	12502.323	CMFileImpl
4	1	951.999	CMFileImpl/ClearMetFile
4	1	2143.400	CMFileImpl/GetMetRec
2	1	479.541	CMFileImpl/StoreMetRec
1	1	175.663	CMFileImpl/EOFMetFile
2	1	533.290	CMFileImpl/ResetMetFile
3	1	512.779	CMFileImpl/CloseMetFile
4	1	1367.700	CMFileImpl/OpenMetFile
34	1	27005.613	AnalyzerImpl
7	1	3482.928	ProcMetricsImpl/PmPush/PmInit
4	1	2049.399	ProcMetricsImpl/PmPush
6	1	5941.321	AnalyzerImpl/InitializeErrors
4	1	1681.599	ProcMetricsImpl/PmPop
11	1	17952.277	AnalyzerImpl/MakeForm
9	1	3602.505	AnalyzerImpl/EnumerateFiles
1	1	67.500	AnalyzerImpl/EnumerateFiles/AddEnumerating
5	1	4319.317	ProcMetricsImpl/PmDump
11	1	1465.504	ProcMetricsImpl
4	1	4383.412	ScannerImpl/AppendOctal
2	1	1808.729	ScannerImpl/EnterLit
1	1	119.589	ScannerImpl/ScanStats
1	1	553.301	ScannerImpl/ItemHandleToStreamIndex
57	1	55864.259	ScannerImpl
2	1	1162.287	UtilsImpl/StringEqual
2	1	1306.190	UtilsImpl/StringLess
3	1	629.469	AnalyzerImpl/FreeNameDescriptor
4	1	326.231	UtilsImpl
1	1	39.302	AnalyzerImpl/ExecutiveProc
1	1	71.323	AnalyzerImpl/WindowOutput

Sort by Effort :

LOC	CC	EFFORT	Procedure Name
320	210	4662495.500	Grammar/ProcessQueue
252	196	2424798.000	ScannerImpl/Atom
231	151	1970947.625	Grammar/ProcessQueueCont
51	35	294474.718	ScannerImpl/CollectNumber
141	1	240554.500	CMStatsImpl/StatsImpress
70	23	220672.203	ParserImpl/Parse
49	28	192890.203	CMStatsImpl/Overlap
60	29	175504.125	ParserImpl/Recover
96	1	157919.593	ParserImpl
29	19	127131.421	ScannerImpl/ScanFloating
27	1	122436.335	EncodeImpl/InitEncodeTable
35	7	98389.132	CMStatsImpl/ReadMetrics
32	25	91114.359	AnalyzerImpl/RunIt
35	16	81116.781	CMStatsImpl/QuickCC
33	7	75960.078	UtilsImpl/RealToString
32	12	72341.656	ParserImpl/GrowTree
27	13	62963.859	ScannerImpl/ErrorContext
23	10	60963.832	CMStatsImpl/QuickName
11	1	59653.515	McCabeImpl/McDump
15	15	57726.308	ScannerImpl/ScanHex
57	1	55864.269	ScannerImpl
22	6	51668.382	ProcMetricsImpl/PmImpress
20	10	38852.316	ParserImpl/RightScan
25	7	38278.285	UtilsImpl/CardToString
21	6	37698.492	HalsteadImpl/HsCompute
19	12	36466.429	ParserImpl/Accept
21	9	35515.578	CMStatsImpl/QuickLOC
21	9	33310.777	CMStatsImpl/QuickEffort
13	11	33145.804	ScannerImpl/ScanDecimal
13	11	33145.804	ScannerImpl/ScanOctal
22	2	31673.464	CMStatsImpl/AllocArrays

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37	5	31019.351	CMStatsImpl/MetricStats
29	10	29655.220	ParserImpl/ExistingConfiguration
34	2	29923.259	CMStatsImpl/MetImpress
15	11	27647.445	AnalyzerImpl/RunIt/BreakupFiles
34	1	27005.613	AnalyzerImpl
14	3	26582.455	EncodeImpl/EncodeId
16	3	26407.884	CMStatsImpl/MakeNewNode
29	3	25308.105	CMStatsImpl/OutSort
16	6	25307.597	ParserImpl/ActOnStack
11	8	25329.330	ScannerImpl/ScanOctalChar
19	6	23037.746	ParserImpl/SyntaxError
14	8	22408.482	ParserImpl/ParseStep
11	5	21177.693	EncodeImpl/DecodeChar
15	3	20339.093	EncodeImpl/DecodeId
24	11	19261.224	AnalyzerImpl/ProcessFile
11	3	19002.236	HalsteadImpl/HsDump
11	1	17862.277	AnalyzerImpl/MakeForm
12	3	17530.996	ParserImpl/ExpandStack
15	4	16419.607	HalsteadImpl/HsOperator
15	4	16419.607	HalsteadImpl/HsOperand
9	5	16213.844	EncodeImpl/EncodeChar
12	7	14510.231	AnalyzerImpl/ProcessFile/CleanUp
17	3	13351.339	AnalyzerImpl/Initialize
15	1	12502.323	CMFileImpl
10	7	11233.350	ParserImpl/AddLeaf
21	2	10766.739	ScannerImpl/ScanInit
9	7	10719.255	ParserImpl/CheckTree
13	3	10600.215	HalsteadImpl/HsCompute/HsFree
6	2	9980.321	AnalyzerImpl/MakeSws
7	2	9743.224	ProcMetricsImpl/PmGetProcName
13	1	9262.550	McCabeImpl/McInit
3	3	8990.468	ParserImpl/TypeSym
11	4	8423.299	ScannerImpl/ResetScanIndex
6	3	8325.503	ParserImpl/ExpandQueue
14	1	8044.816	ParserImpl/ParseInit
6	6	7728.919	ParserImpl/NextRow
5	3	7494.709	ScannerImpl/AppendDecimal
14	4	7249.834	AnalyzerImpl/GenStats
4	2	7202.639	ScannerImpl/AppendHex
5	3	6696.540	ScannerImpl/AppendToScale
7	2	6539.538	ScannerImpl/ExpandBuffer
7	5	6001.291	ParserImpl/FindNode
6	1	5941.321	AnalyzerImpl/InitializeErrors
27	1	5267.874	CMStatsImpl
12	2	5194.714	ParserImpl/DisplayNode
11	3	5190.876	AnalyzerImpl/ClearIt
4	4	5148.029	ParserImpl/RecoverInput
4	2	4598.145	ParserImpl/Allocate
4	1	4383.412	ScannerImpl/AppendOctal
5	1	4319.817	ProcMetricsImpl/PmDump
2	4	4213.928	ParserImpl/GetNTEntry
14	5	3848.032	AnalyzerImpl/Unload
7	4	3765.871	ScannerImpl/FillBuffer
9	1	3603.806	AnalyzerImpl/EnumerateFiles
4	7	3586.635	ScannerImpl/ScanError
7	1	3482.928	ProcMetricsImpl/PmPush/PmInit
2	3	3273.918	ScannerImpl/ValidFraction
5	2	3094.849	McCabeImpl/McCompute
4	1	2143.400	CMFileImpl/GetMetRec
2	3	2090.743	ParserImpl/FreeRowList
4	1	2049.399	ProcMetricsImpl/PmPush
5	1	1913.293	HalsteadImpl/HsInit
8	2	1833.941	CMStatsImpl/OutEncodeMap
10	1	1821.996	Grammar
2	1	1808.729	ScannerImpl/EnterLit
4	2	1796.011	CMStatsImpl/Cleanup
3	3	1787.488	ScannerImpl/Escape
4	1	1681.699	ProcMetricsImpl/PmPop
2	1	1608.906	ParserImpl/LinkHash
8	1	1589.004	EncodeImpl
11	1	1465.634	ProcMetricsImpl
3	2	1391.486	ScannerImpl/CollectNumber/Accept
4	1	1367.700	CMFileImpl/OpenMetFile
2	1	1306.190	UtilsImpl/StringLess
2	1	1162.287	UtilsImpl/StringEqual
4	1	1089.273	Grammar/AssignDescriptors

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   83

```
4      1      951.999    CMFileImpl/ClearMetFile
4      1      917.552    CMStatsImpl/EncodeNewLine
4      1      917.552    CMStatsImpl/MetNewLine
4      1      917.552    CMStatsImpl/StatsNewLine
1      1      802.894    McCabeImpl/McIncrement
3      2      742.585    ParserImpl/Discard
3      2      742.585    ParserImpl/UnDiscard
2      2      738.402    ParserImpl/EraseStack
4      1      713.356    ParserImpl/input
4      3      713.113    AnalyzerImpl/GenerateStats
1      1      632.279    ProcMetricsImpl/PmOperand
1      1      632.279    ProcMetricsImpl/PmOperator
3      1      629.469    AnalyzerImpl/FreeNameDescriptor
3      2      619.347    ScannerImpl/ScanReset
1      1      553.801    ProcMetricsImpl/PmLines
1      1      553.801    ScannerImpl/ItemHandleToStreamIndex
3      2      548.259    AnalyzerImpl/Initialize/Cleanup
2      1      533.290    CMFileImpl/ResetMetFile
1      1      528.000    ProcMetricsImpl/PmMcCabe
3      1      512.779    CMFileImpl/CloseMetFile
2      1      479.541    CMFileImpl/StoreMetRec
1      2      462.857    ScannerImpl/NextChar
3      3      431.754    AnalyzerImpl/Run
5      1      427.400    HalstadImpl
3      3      411.194    AnalyzerImpl/ClearOutputFile
7      1      382.378    Grammar/Initialize
4      1      325.231    UtilsImpl
4      1      313.684    McCabeImpl
1      1      284.282    CMStatsImpl/StatsWrite
1      1      284.282    CMStatsImpl/EncodeWrite
1      1      284.282    CMStatsImpl/MetWrite
1      2      233.022    ParserImpl/EraseQueue
1      1      217.944    ParserImpl/Advance
1      1      175.663    CMFileImpl/EOFMetFile
2      1      145.296    ParserImpl/ParseReset
1      1      119.589    ParserImpl/NewLine
1      1      119.589    ScannerImpl/ScanStats
1      1      95.097     ParserImpl/ParserID
1      1      71.323     AnalyzerImpl/WindowOutput
1      1      67.500     AnalyzerImpl/EnumerateFiles/AddEnumerating
1      1      67.500     ParserImpl/InputLoc
1      1      39.302     AnalyzerImpl/ExecutiveProc
```

Appendix C.   Statistical Report Generated by the Code Metric Analyzer.   84

Appendix D.   Code Metric Analyzer User's Guide

Mesa Code Metrics Analyzer

User's Guide

June, 1988

John Lewis

Introduction

The Mesa Code Metrics Analyzer computes software quality metrics for arbitrary Mesa source code which indicate the level of complexity of the software. This data can be used to identify highly error-prone code, and therefore indicate where redesign and testing efforts should be concentrated.

The metrics calculated using this tool are Lines of Code, Halstead's Software Science indicators (specifically Effort), and McCabe's Cyclomatic Complexity metric. These metrics are calculated for each procedure in the analyzed software.

Once data has been collected across a set of procedures, a statistical report can be generated to assist the metrics interpretation. Sorts are performed for each metric, and overlaps are computed to indicate the set of procedures that are considered most complex by certain combinations of the metrics. The average, standard deviation, min and max are also computed for each metric.

Additionally, this tool can create data files containing the metrics information which are readable by another metrics analysis tool currently residing at Virginia Tech. This data can be encoded to protect any proprietary information.

This document is designed to assist the user of the Mesa Code Metrics Analyzer in generating and interpreting the metrics data.

See the Mesa Code Metrics Analyzer Implementation Guide for additional information on the internal makeup, techniques, and data structures used in the analyzer.

Input

The following information is used as input to the Mesa Code Metrics Analyzer:

Mesa Source Code

The source code analyzed is assumed to be syntactically correct, although the analyzer will detect syntax errors and abort processing. Any Mesa source code may be processed, including definitions files, but metrics are only calculated for executable procedures. The input file names are listed in the form subwindow of the Mesa Code Metrics Analyzer tool and may be specified using lists, wildcard characters, or by using ToolDriver.

Statistical Processing Constraints

Parameters controlling the statistical and additional reports are specified in the form subwindow of the tool. They include:

1) a numeric indicating the percentage of total procedures that should be considered when computing the overlap of highly complex procedures across the metrics,

2) a flag indicating if the additional data file for the Virginia Tech metrics analyzer should be created, and

3) a flag indicating if the output data should be encoded to protect proprietary information.

A complete explanation of the form subwindow fields which control the input and processing of the Mesa Code Metrics Analyzer is given below.

Output

The following output files are generated by the Mesa Code Metrics Analyzer:

CodeMetrics.data

> This binary file contains the raw metrics data for each procedure analyzed. It serves as input to the statistical report generating software. The data for each file as processed is appended to this file until cleared by the Clear! command. Once cleared, the data is destroyed. If further analysis is desired on the current set of procedures, this file should be renamed or moved off the search path prior to executing the Clear! command.

CodeMetrics.stats

> This file contains the statistical report generated to assist in the interpretation of the metric data. This file is generated as a result of executing the Stats! command. A complete explanation of the report is given in the following section.

CodeMetrics.out

> If the Backend Output boolean field is set in the form subwindow of the tool when the Stats! command is executed, this file will be generated. It contains the code metrics data in a text format which is readable by another metrics analysis tool currently residing at Virginia Tech. This file should not be generated if the data is not to be processed by the other tool.

CodeMetrics.encode

> If the Encode boolean field is set when the Stats! command is executed, all procedure names in the text output files will be encoded to protect proprietary information. In addition, this file will be generated. It contains a listing of the encoded procedure aliases in alphabetical order and their correct names. Encoding should be done only if the data is to be further analyzed off site or by non-cleared personnel. This file will then assist in mapping the encoded analysis back to the proper software.

CMAnalyzer.Log

This file contains a log of the processing of the Mesa Code Metrics Analyzer tool. Processing information is also output to the tool's file subwindow.

The Metrics Statistics Report

Executing the Stats! command in the form subwindow creates the text file CodeMetrics.stats which contains a statistical report of the metrics data currently stored in CodeMetrics.data. The analysis is based on the Lines of Code (LOC), Halstead's Effort, and McCabe's Cyclomatic Complexity metrics. The report is separated into three sections.

The first section gives an average, standard deviation, minimum and maximum values for each of the metrics. It also reports the total number of procedures that are considered in the statistical analysis.

The second section reports the procedures which overlap some top percentage of the highly complex procedures in various combinations of the metrics. The overlaps are computed by sorting the procedures by each of the metrics, then considering only a certain percentage of the data as specified in the Percent Overlap field of the form subwindow. Of this percentage, lists of procedures are constructed which appear in the highest values of all metrics, and of any combination of two metrics.

For example, if the Percent Overlap field contained the value 50, the top half of the procedures in each of the metrics are compared and four lists are reported: a list of the procedures who appeared in the top half of all three metrics, the procedures who appear in the top half of only LOC and Cyclomatic Complexity, the procedures who appear in the top half of only LOC and Effort, and finally the procedures who appear in the top half of only Cyclomatic Complexity and Effort.

The third section contains four sorts of all procedures. The data is sorted by procedure name and by each of the three metrics.

Any time a list of procedures is given in the report, the associated metric values are supplied as well.

Analyzer Tool Fields

The following are the fields in the form subwindow of the Code Metrics Analyzer which control its operation:

Mesa Source Files:

This field accepts the file or files of Mesa source code to be analyzed. Files may be specified using lists and/or wildcards. An extension of .mesa is assumed if none is provided.

Go!

This command item performs the source code analysis on the files specified in the Mesa Source Files field. LOC, Halstead, and McCabe metrics are calculated for each procedure in the specified files. The analysis data of each run is appended to any previous results since the last Clear! execution. Only raw data is generated with this command; no reports are created. The metrics data is stored in the binary file CodeMetrics.data.

Stats!

This command performs a statistical analysis on the metrics data generated by the source code analysis (Go! command). The report is written to the text file CodeMetrics.stats. A complete explanation of the report is given in the previous section. Each execution of Stats! overwrites any previous report.

Clear!

Execution of Clear! removes all data previously generated by the source code analysis stored in CodeMetrics.data. The data file should be saved in another file or removed from the search path prior to executing Clear! if that analysis will be needed in the future.

Percent Overlap =

This field accepts a numeric indicating the percentage of the total number of analyzed procedures that are considered when computing the overlap between the highly complex procedures. This field only affects the execution of the Stats! command. If the field contains a value that is less than one or greater than 100, a value of 100 percent is used. This field defaults to 10 percent.

BackEnd Output

This boolean item only affects the execution of the Stats! command. If the flag is set when Stats! is run, a text data file is created which serves as input to a backend metrics analysis tool. The data file is called CodeMetrics.out and will rewrite any old data in the file. This field defaults to false.

Encode

Similar to the BackEnd Output field, this boolean item only affects the execution of the Stats! command. If it is set when Stats! is executed, then any module and procedure names are encoded in the statistics output report and in the backend data file. Also, this flag will cause another text file to be created, called CodeMetrics.encode, which lists the procedure names in normal and encoded form in alphabetical order by alias. This field defaults to false.

Restrictions and Limitations

Several restrictions currently exist in the Mesa Code Metrics Analyzer. They are listed below.

1) The source code analyzed must be syntactically valid. The analyzer will abort processing on the first syntax error detected.

2) To statistically analyze groups of source code procedures at various hierarchial levels without having to reanalyze the source code, the smallest groups must be analyzed (saving the data), then manually appended together to form larger groups which can then be analyzed.

3) The largest group of procedures which can be processed in one analysis is limited by the amount of available memory on the workstation.

3) Executing the Clear! command destroys all data in the current data file. The data file must be renamed or moved off the search path if it will be needed in the future.

Appendix E.   Code Metric Analyzer Implementation Guide

Mesa Code Metrics Analyzer

Implementation Guide

June, 1988

John Lewis

Introduction

The Mesa Code Metrics Analyzer processes source code written in the Mesa programming language and produces software quality metrics for individual procedures in the code. These values identify code which is highly complex and error-prone, therefore where redesign and testing efforts should be concentrated. The analyzer also produces a statistical report of the metrics data collected.

This document serves as a guide to the implementation of the analyzer, including its makeup, techniques, and data structures. It should be used to assist any maintenance activities on the analyzer.

See the Mesa Code Metrics Analyzer User's Guide for additional information on the tool's use and data interpretation.

Impl / Interface Relationships

The following describe the important files used in the Mesa Code Metrics Analyzer and their relationships:

INTERFACE	EXPORTED BY
ProcMetrics.mesa	ProcMetricsImpl.mesa
	HalsteadImpl.mesa
	McCabeImpl.mesa
	CMStatsImpl.mesa
Utils.mesa	UtilsImpl.mesa
	EncodeImpl.mesa
	CMFileImpl.mesa
	AnalyzerImpl.mesa
Parser.mesa	ParserImpl.mesa
	ScannerImpl.mesa
	Grammar.mesa

Configuration File: CMAnalyzer.config

Executable Image: CMAnalyzer.bcd

DF File: CMAnalyzer.df

Module Descriptions

The following are the modules which make up the Mesa Code Metrics Analyzer:

ProcMetricsImpl.mesa

This file contains the high level metrics data collection routines. As the Mesa grammar is perused while parsing the source file, calls are made to these routines to collect the appropriate information that will eventually yield the LOC, Halstead's effort, and McCabe's Cyclomatic Complexity metrics. These routines rely heavily on the lower level collection procedures in HalsteadImpl.mesa and McCabeImpl.mesa. Also included in this file is the routine which calculates a procedure's metrics once the data has been collected and writes it to the binary data file CodeMetrics.data. The module is exported to ProcMetrics.mesa.

HalsteadImpl.mesa

The routines in this file collect the information necessary to calculate the Halstead Software Science indicators, specifically lists of unique operators and operands in the code. These routines are called by the higher level control routines in ProcMetricsImpl.mesa. This module is exported to ProcMetrics.mesa.

McCabeImpl.mesa

The routines in this file collect the information necessary to calculate McCabe's Cyclomatic Complexity metric, specifically the count of decision points in the code. These routines are called by the higher level control routines in ProcMetricsImpl.mesa. This module is exported to ProcMetrics.mesa.

CMStatsImpl.mesa

This module controls all processing performed when the Stats! command is executed. This processing includes the generation of the statistical report of the data currently residing in CodeMetrics.data. Also, the data file CodeMetrics.out is created if the Backend Output flag is set in the form subwindow. All output is encoded if the boolean item Encode in in the form subwindow is set. The processing for the statistical report generation make up the majority of routines in this file, including procedures to sort and calculate overlaps of the highest metric indicators. The main data structures used in this file are described below. This module is exported to ProcMetrics.mesa.

EncodeImpl.mesa

This file contains the routines which encode identifier names in order to protect proprietary information. The encoding keys and mapping techniques used are described in this module. This module is exported to Utils.mesa.

UtilsImpl.mesa

This module contains utility routines used throughout the analyzer as needed. This module is exported to Utils.mesa.

CMFileImpl.mesa

This file contains the routines which control the intermediate metrics data file CodeMetrics.data. The data file is binary, and stores one record for each procedure analyzed. The record contains the essential metrics data and the procedure's name stored as a packed array of characters. As procedures are analyzed, their information is appended to the existing data in the data file. The Clear! command destroys all information in this file, essentially providing the user a clean slate to begin a new batch of processing. This module is exported to Utils.mesa.

ParserImpl.mesa

This module is a modified version of the parser used by the Mesa compiler. It has been modified to maintain a circular stack of identifiers used in the metrics analysis. This file controls the parsing of the input source code. All input is assumed to be syntactically correct, although the parser will detect syntax errors and abort processing. This module is exported to Parser.mesa

ScannerImpl.mesa

This file is a modified version of the lexical analyzer used by the Mesa compiler. Its routines are used in conjunction with the parser to return the individual language tokens. It has been modified very little. This module is exported to Parser.mesa.

Grammar.mesa

This file contains the Mesa grammar specification, and serves as input to the Parser Generator System (PGS) which creates the LALR tables used by the parser. Also, the routines are set up such that code is executed after each production in the procedure is reduced. This code is primarily calls to the routines in ProcMetricsImpl.mesa which gather the appropriate metrics data. As each procedure is exited, the data for that procedure is processed and the metrics data is appended to CodeMetrics.data. This module is exported to Parser.mesa.

AnalyzerImpl.mesa

This module creates the actual analyzer tool itself, sets up the variables associated with the fields of the form subwindow, and calls the appropriate routines as commands are executed. It is the module started when the analyzer is invoked. This module exports data to Utils.mesa.

Analyzer Tool Fields

The following are the fields in the form subwindow of the Code Metrics Analyzer which control its operation:

Mesa Source Files:

This field accepts the file or files of Mesa source code to be analyzed. Files may be specified using lists and/or wildcards. An extension of .mesa is assumed if none is provided.

Go!

This command item performs the source code analysis on the files specified in the Mesa Source Files field. LOC, Halstead, and McCabe metrics are calculated for each procedure in the specified files. The analysis data of each run is appended to any previous results since the last Clear! execution. Only raw data is generated with this command; no reports are created. The metrics data is stored in the binary file CodeMetrics.data.

This command executes the procedure Run in AnalyzerImpl.mesa. The procedure detaches a process to perform the analysis. The processing speed of the analysis obviously depends on the number of procedures analyzed and their relative size. Processing an average file of ten procedures can take between five seconds and two minutes.

Stats!

This command performs a statistical analysis on the metrics data generated by the source code analysis (Go! command). The report is written to the text file CodeMetrics.stats. A complete explanation of the report is given in the Mesa Code Metrics Analyzer User's Guide. Each execution of Stats! overwrites any previous report.

This command executes the procedure GenerateStats in AnalyzerImpl.mesa. The procedure detaches a process to perform the statistical report generation. The processing speed of this function depends on the amount of data in CodeMetrics.data and the percent overlap specified. To generate a report for 800 procedures with ten percent overlap takes ten to fifteen minutes.

Clear!

Execution of Clear! removes all data previously generated by the source code analysis stored in CodeMetrics.data. The data file should be saved in another file or removed from the search path prior to executing Clear! if that analysis will be needed in the future.

This command executes the procedure ClearMetData in AnalyzerImpl.mesa. The procedure detaches a process to perform the clearing function. The processing takes only a few seconds, no matter how much information is in the data file.

Percent Overlap =

This field accepts a numeric indicating the percentage of the total number of analyzed procedures that are considered when computing the overlap between the highly complex procedures. This field only affects the execution of the Stats! command. If the field contains a value that is less than one or greater than 100, a value of 100 percent is used. This field defaults to ten percent.

BackEnd Output

This boolean item only affects the execution of the Stats! command. If the flag is set when Stats! is run, a text data file is created which serves as input to a backend metrics analysis tool. The data file is called CodeMetrics.out and will rewrite any old data in the file. This field defaults to false.

Encode

Similar to the BackEnd Output field, this boolean item only affects the execution of the Stats! command. If it is set when Stats! is executed, then any module and procedure names are encoded in the statistics output report and in the backend data file. Also, this flag will cause another text file to be created, called CodeMetrics.encode, which lists the procedure names in normal and encoded form in alphabetical order by alias. This field defaults to false.

Main Data Structures

Several fundamental data structures are used to collect, process and statistically analyze the metrics data. These are described below:

METRICS COLLECTION

pm

defined: ProcMetricsImpl.mesa
used: Grammar.mesa, ProcMetricsImpl.mesa, HalsteadImpl.mesa, McCabeImpl.mesa

pm is a record of procedure metrics data, used later to calculate the complete metric values. It contains a procedure name, a lines of code count, two lists of unique operators and operands with associated counts, and counts of decision points encountered. The lists of operators and operands are used to calculate the Halstead metrics, and the decision counts are used for McCabe's Cyclomatic Complexity. Each pm record stores only one procedure's data.

_ pmStack _

    defined: ProcMetricsImpl.mesa
    used: Grammar.mesa, ProcMetricsImpl.mesa

This structure is a simple array and is used as a stack of the pm records so that
nested procedures can be handled properly. As a new procedure is entered, the
current pm record is pushed on the stack and a new one initialized. The full path
name of a given procedure is obtained from all pm records on the pm stack.

STATISTICAL ANALYSIS

metList

    defined: CMStatsImpl.mesa
    used: CMStatsImpl.mesa

metList is a linked list of records containing the complete metrics values for the
procedures to be analyzed. The data is read from the binary data file
CodeMetrics.data. The name in each node of the list is the name of the
procedure, and is encoded if the Encode boolean item is set in the form
subwindow of the analyzer tool. This list serves as a organization of the metrics
information prior to being statistically analyzed.

nameSort, locSort, ccSort, effortSort

    defined: CMStatsImpl.mesa
    used: CMStatsImpl.mesa

Each of these structures are unique Mesa sequences containing pointers to the
nodes in metList. They are used to sort the metrics information by procedure
name, Lines of Code, Cyclomatic Complexity, and Halstead's Effort, respectively.
Using sequences of pointers allows the data to be stored only once and still allow
the sorting to be completely performed on all criteria. Also, the sorting process
only needs to swap pointers using this method.

olapall, olaplc, olaple, olapce

    defined: CMStatsImpl.mesa
    used: CMStatsImpl.mesa

Similar to the sorting sequences, these sequences are used to store pointers to
the nodes in metList. The procedures indicated in each of these sequences
represents the overlap calculations of the highest metrics values of all three
metrics, LOC / CC, LOC / Effort, and CC / Effort, respectively. These sequences are
sorted by procedure name prior to output to the statistical report file.

Appendix F.   Regression Equation Analysis

The following pages contain the statistical evaluation of the regression equations considered for models to predict errors at the module level. The R-squared and Mean Squared Error (MSE) values are given in the first two matrices. The column titled PARAMETER ESTIMATE are the coefficients for the variables in the equation. The equations were deliberatly calculated without an intercept to be consistent with the semantics of the analysis. The actual and predicted values for each observation are given in the following matrix.

The equations presented in chapter 4 were chosen from this set of analyzed equations. Choices were made by considering the equations with the best evaluatory statistics and how well each predicted actual errors.

DEP VARIABLE: ERR

MODEL INCLUDING CLUS V LOC

16.55 FRIDAY, DECEMBER 9, 1988

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	25247.06404	8415.68801	15.578	0.0113
ERROR	4	2160.93596	540.23399		
U TOTAL	7	27408.00000			

ROOT MSE	23.24293	R-SQUARE 0.9212
DEP MEAN	43.42857	ADJ R-SQ 0.8620
C.V.	53.51991	

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
CLUS	1	0.000050015	0.000023188	2.157	0.0972	3.83382819
V	1	0.00081612	0.000092060	0.887	0.4254	100.97383
LOC	1	-0.00429482B	0.007439021	-0.577	0.5946	108.67361

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	5.2424	7.0247	-14.2610	24.7459	-62.1723	72.6571	28.7576	22.1560
2	31.0000	34.7324	17.8995	-14.9640	84.4288	-46.7176	116.2	-3.7324	14.8270
3	147.0	145.6	23.2261	81.1311	210.1	54.3874	236.8	1.3818	0.8863
4	27.0000	28.8534	15.8750	-1.6692	75.3759	-38.3021	112.0	-9.8534	18.6472
5	53.0000	28.1042	12.1337	-5.5839	61.7922	-44.6917	100.9	19.8244	19.8258
6	0	24.2680	24.2269	-23.5810	72.0970	-56.0562	104.6	-24.2680	15.6034
7	12.0000	8.6979	8.6604	-15.5468	32.5426	-60.3680	77.3658	3.5021	21.5692

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.2980		0.056
2	-0.2517		0.031
3	1.5648		563.065
4	-0.5284		0.052
5	1.2558		0.197
6	-1.5553		0.983
7	0.1624		0.001

SUM OF RESIDUALS   20.68556
SUM OF SQUARED RESIDUALS   2160.936
PREDICTED RESID SS (PRESS)   919291.7

DEP VARIABLE: ERR

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	26784.06726	8928.02242	57.257	0.0010
ERROR	4	623.93274	155.98318		
U TOTAL	7	27408.00000			

ROOT MSE	12.48932	R-SQUARE	0.9772
DEP MEAN	43.42857	ADJ R-SQ	0.9602
C.V.	28.75831		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
HOOD	1	1.41578E-07	4.46785E-08	3.169	0.0339	454.57362
CLUS	1	-0.00036681 5	0.00013608 7	-2.695	0.0543	454.35062
INFO	1	2.47384346	0.68897862	3.591	0.0229	1.46258190

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	19.5364	5.5451	4.1410	34.9318	-18.4031	57.4759	14.4636	11.1909
2	31.0000	44.3217	8.0555	21.9564	66.6869	-3.0592	85.5842	-13.3217	9.5442
3	147.0	146.3	12.4611	111.7	180.9	97.2950	195.3	0.7219	0.8393
4	27.0000	34.3371	5.4056	19.3290	49.3452	-3.6669	72.3411	-7.3371	11.2589
5	53.0000	40.5574	6.8303	21.5936	59.5212	1.0351	80.0797	12.4426	11.0456
6	0	4.9632	10.1764	-23.2905	33.2169	-39.7655	49.6919	-4.9632	7.2405
7	12.0000	13.8608	6.1319	-3.1639	30.8855	-26.7685	52.4902	-1.8608	10.8804

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.2925	**|	0.137
2	-1.3958	**|	0.463
3	0.8601	|*	54.345
4	-0.6517	*|	0.033
5	1.1900	|**	0.201
6	-0.6855	*|	0.309
7	-0.1710	|	0.003

SUM OF RESIDUALS	0.1452705
SUM OF SQUARED RESIDUALS	623.9327
PREDICTED RESID SS (PRESS)	27011.93

Appendix F. Regression Equation Analysis.

DEP VARIABLE: ERR

MODEL INCLUDING MOOD CLUS V LOC

16:55 FRIDAY, DECEMBER 9, 1988

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	27347.80201	5469.56040	181.719	0.0055
ERROR	2	60.19799066	30.09899533		
U TOTAL	7	27408.00000			

ROOT MSE	5.486255	R-SQUARE	0.9978	
DEP MEAN	43.42857	ADJ R-SQ	0.9923	
C.V.	12.63282			

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
MOOD	1	2.89970E-07	4.05482E-08	7.151	0.0190	1940.33762
CLUS	1	-0.00081881'4	0.00012545458	-6.527	0.0227	2014.37172
V	1	-0.00018686869	0.00004525278	-4.127	0.0540	438.41026
LOC	1	0.01425800	0.00380205236	3.750	0.0643	509.56633
INFO	1	2.99085997	0.76461233	3.912	0.0596	9.33505926

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	29.1812	4.2968	10.6933	47.6692	-0.8027	59.1651	4.8188	3.4112
2	31.0000	31.5741	4.8411	10.7441	52.4041	0.0921	63.0561	-0.5741	2.5812
3	147.0	5.4858	123.4	170.6	113.6	180.4	-0.0316	0.0691	
4	53.0000	5.5656	31.1540	40.8372	-2.65/5	53.6486	-0.0046	0.1696	
5	-0.8502	5.3163	-22.6125	76.8700	-21.1341	86.8751	-1.5044	4.1696	
6	12.0000	17.7141	5.0578	-22.6125	20.9120	-32.9567	31.2562	1.0046	3.3550
7		3.4560	2.8442	32.5861	-10.1847	45.6130	-0.8502	2.1254	
							-5.7141	4.2609	

OBS	STUDENT RESIDUAL	-2 -1 -0 1 2	COOK'S D
1	1.4126		0.633
2	-0.2224		0.035
3	-0.4581	**	264.637
4	-0.3608	*	0.019
5	-0.7414		1.692
6	0.4000	**	0.181
7	-1.3411		0.237

SUM OF RESIDUALS	-0.15101B
SUM OF SQUARED RESIDUALS	60.19799
PREDICTED RESID SS (PRESS)	40394.72

Appendix F.   Regression Equation Analysis.

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ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	4	26835.12484	6708.78121	35.132	0.0075
ERROR	3	572.87516	190.95839		
U TOTAL	7	27408.00000			

ROOT MSE	13.81877	R-SQUARE	0.9791
DEP MEAN	43.42857	ADJ R-SQ	0.9512
C.V.	31.81953		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
MOOD	1	1.43684E-07	4.96018E-08	2.897	0.0627	457.658867
CLUS	1	-0.000363701	0.000150693	-2.414	0.0947	458.082232
LOC	1	-0.001066217	0.002061981	-0.517	0.6408	23.621737713
INFO	1	5.33007607	1.91119886	1.769	0.1751	9.193046757

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	23.8256	10.3175	-9.0097	56.6609	-31.0583	78.7095	10.1744	9.1928
2	31.0000	45.0256	9.0163	16.3312	73.7200	-7.6859	97.5370	-14.0256	10.4721
3	147.0	146.7	13.8165	102.8	190.7	86.5512	208.9	0.2592	0.2486
4	27.0000	31.4208	8.2208	5.2583	57.5834	-19.7511	82.5927	-4.4208	11.1075
5	53.0000	37.9258	9.1113	8.9290	66.9225	-14.7515	90.6031	15.0742	10.3895
6	0	2.0174	12.6188	-38.1421	42.1768	-57.5382	61.5729	-2.0174	5.6324
7	12.0000	16.6612	8.6811	-10.9664	44.2888	-35.2750	68.5974	-4.6612	10.7516

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.1068	|**	0.386
2	-1.3393	**|	0.332
3	1.0427	|**	839.863
4	-0.3980	*|	0.022
5	1.4509	|**	0.405
6	-0.3582	*|	0.161
7	-0.4335	*|	0.031

SUM OF RESIDUALS	0.3828711
SUM OF SQUARED RESIDUALS	572.8752
PREDICTED RESID SS (PRESS)	643812.8

Appendix F.   Regression Equation Analysis.

DEP VARIABLE: ERR

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	23772.14308	7924.04769	8.718	0.0315
ERROR	4	3635.85692	908.96423		
U TOTAL	7	27408.00000			

ROOT MSE	30.14903	R-SQUARE	0.8673
DEP MEAN	43.42857	ADJ R-SQ	0.7679
C.V.	69.4212		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
LOC	1	0.01245596	0.01119220	1.114	0.3278	146.20381
E	1	0.00001661	0.00001246692	0.935	0.4026	13.51939132
CC	1	-0.02369487	0.02540866	-0.933	0.4038	160.72568

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	14.7925	3.5058	5.0589	24.5261	-69.4775	99.0626	19.2075	29.9445
2	51.0000	24.3799	21.0698	-34.1184	82.8781	-77.7613	126.5	6.6201	21.5645
3	147.0000	116.6	24.5708	48.3385	184.8	8.5744	224.5	30.4429	17.4711
4	27.0000	43.0567	20.8323	-14.7823	100.9	-58.6883	144.8	-16.0567	21.7940
5	53.0000	76.2887	26.8647	1.7568	150.8	-35.7903	188.4	-23.2887	13.7231
6	0	38.6008	21.0920	-19.9591	97.1608	-63.5557	140.8	-38.6008	21.5428
7	12.0000	14.4753	8.2125	-8.3260	37.2766	-72.2806	101.2	-2.4753	29.0089

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	0.6414		0.002
2	0.3070	|*	0.030
3	1.7425	|***	2.002
4	-0.7425	*|	0.165
5	-1.6970	***|	3.673
6	-1.7918	***|	1.026
7	-0.0853		0.000

SUM OF RESIDUALS	-24.151
SUM OF SQUARED RESIDUALS	3635.857
PREDICTED RESID SS (PRESS)	28066.86

Appendix F.   Regression Equation Analysis.   107

MODEL INCLUDING LOC CC H

DEP VARIABLE: ERR

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	24220.93598	8073.64666	10.133	0.0243
ERROR	4	3187.06002	796.76501		
U TOTAL	7	27408.00000			

ROOT MSE	28.22703	R-SQUARE	0.8837
DEP MEAN	43.42857	ADJ R-SQ	0.7965
C.V.	64.99644		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
LOC	1	0.008687947	0.01085061	0.801	0.4682	156.76633
CC	1	-0.05155654	0.03605974	-1.430	0.2260	369.29858
H	1	0.001469135	0.001175871	1.249	0.2796	331.95776

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	-0.4814	13.5682	-38.1523	37.1896	-87.4349	86.4722	34.4814	24.7521
2	31.0000	30.9530	21.0222	-27.4133	89.3193	-66.7631	128.7	0.0470	18.8569
3	147.0	151.7	24.7844	62.9314	200.6	-27.4509	236.0	-4.6570	13.5092
4	27.0000	35.7534	19.4164	-18.1544	89.6613	-59.3669	130.9	-8.7534	20.4882
5	53.0000	55.9397	13.0185	19.7950	92.0843	-30.3636	142.2	-2.9397	25.0456
6	0	38.6839	17.0037	-8.5253	85.8932	-52.8066	130.2	-38.6839	22.5508
7	12.0000	-1.5502	17.7311	-50.7791	47.6787	-94.0991	90.9987	13.5502	21.9630

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.3931	| |***	0.194
2	.0024936	| |	0.000
3	-1.1294	| **|	1.431
4	-0.4272	| *|	0.055
5	-0.1174	| |	0.001
6	-1.7169	|***|	0.560
7	0.6170	| |*	0.083

SUM OF RESIDUALS	12.9585
SUM OF SQUARED RESIDUALS	3187.06
PREDICTED RESID SS (PRESS)	10925.16

Appendix F. Regression Equation Analysis.

DEP VARIABLE: ERR

MODEL INCLUDING V CC LOC N

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	4	24398.74449	6099.68612	6.081	0.0850
ERROR	3	3009.25551	1003.08517		
U TOTAL	7	27408.00000			

ROOT MSE	31.67152	R-SQUARE	0.8902
DEP MEAN	43.42857	ADJ R-SQ	0.7458
C.V.	72.92784		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
V	1	0.000170647	0.00040405317	0.421	0.7021	1054.14871
CC	1	-0.04679016	0.04201406	-1.114	0.3466	398.21178
LOC	1	0.00936093	0.01227904	0.762	0.5013	159.46517
N	1	0.00026245	0.003147006	0.085	0.9379	1888.64722

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	2.5959	16.8876	-51.1489	56.3407	-111.6	116.8	31.4041	26.7935
2	31.0000	34.4507	25.0078	-45.1365	114.0	-93.970	162.9	-3.4507	19.4364
3	147.0	127.6	29.4918	33.7509	221.5	-10.1188	265.3	19.3915	11.5664
4	34.0000	34.8770	31.8770	-34.7107	104.5	-87.5902	157.4	-7.9129	22.9015
5	53.0000	53.0159	30.0913	-28.6810	162.8	-72.0186	206.1	-0.0159	9.8792
6	12.0000	34.7912	21.2010	-32.6810	102.3	-86.5021	156.1	-32.6810	23.5287
7		-0.8691	19.9605	-64.3954	62.6552	-120.0	118.3	12.8691	24.5899

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.1721	|**	0.136
2	-0.1776	|	0.013
3	1.6794	|***	4.600
4	-0.3455	|	0.027
5	-1.4187	**|	4.669
6	-1.4787	**|	0.444
7	0.5233	|*	0.045

SUM OF RESIDUALS   3.493959
SUM OF SQUARED RESIDUALS   3009.256
PREDICTED RESID SS (PRESS) 48705.45

Appendix F.   Regression Equation Analysis.   109

DEP VARIABLE: ERR

MODEL INCLUDING LOC E CC H   17.04 FRIDAY, DECEMBER 9, 1988

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	4	24451.53254	6112.88313	6.203	0.0828
ERROR	3	2956.46746	985.48915		
U TOTAL	7	27408.00000			

ROOT MSE	31.3925	R-SQUARE	0.8921
DEP MEAN	43.42857	ADJ R-SQ	0.7483
C.V.	72.28537		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|	VARIANCE INFLATION
LOC	1	0.00950837b	0.01218605	0.780	0.4921	159.86312
E	1	6.87218E-07	.0000142069	0.484	0.6617	16.18726759
CC	1	-0.04907806	0.04042960	-1.214	0.3116	375.32677
H	1	0.00188125	0.00430964	0.830	0.4673	397.46514

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	1.9431	15.9004	-48.6600	52.5462	-110.0	113.9	32.0569	27.0678
2	31.0000	31.0939	23.3816	-43.3179	105.5	-93.6792	155.7	-0.0939	20.9274
3	147.0	127.6	28.8486	35.8143	219.4	-8.0605	263.3	19.3751	12.3794
4	27.0000	38.5572	22.3582	-32.5978	109.7	-84.0983	161.2	-11.5572	22.0363
5	53.0000	68.3877	29.5273	-25.5828	162.4	-68.7683	205.5	-15.3877	10.6597
6	0	32.0797	23.3240	-42.1489	106.3	-92.3840	156.5	-32.0797	21.0114
7	12.0000	-0.4079	19.8605	-63.6158	62.7979	-118.6	117.8	12.6079	24.3116

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.1843	| |**	0.121
2	-.004482	| |	0.000
3	1.5651	| |***	0.326
4	-0.5245	| *|	0.071
5	-1.4435	|***|	0.997
6	-1.5268	|***|	0.718
7	0.5104	| *|	0.043

SUM OF RESIDUALS	4.721444
SUM OF SQUARED RESIDUALS	2956.467
PREDICTED RESID SS (PRESS)	41299.33

Appendix F.   Regression Equation Analysis.

DEP VARIABLE: ERR

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	24454.75420	4890.95084	3.312	0.2480
ERROR	2	2953.24580	1476.62290		
U TOTAL	7	27408.00000			

ROOT MSE	38.42685	R-SQUARE	0.8922
DEP MEAN	43.42857	ADJ R-SQ	0.6229
C.V.	88.48288		

NOTE: NO INTERCEPT TERM IS USED. R-SQUARE IS REDEFINED.

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0, PARAMETER=0	PROB > |T|	VARIANCE INFLATION
V	1	-0.00059867	0.001281682	-0.047	0.9670	7160.64980
CC	1	-0.05004513	0.05364521	-0.953	0.4494	441.016660
LOC	1	0.00950050829	0.01491676	0.637	0.5892	159.865526
H	1	0.001530184	0.007529678	0.203	0.8578	7344.74464
E	1	8.82720E-07	0.000045238	0.195	0.8636	109.955424

OBS	ACTUAL	PREDICT VALUE	STD ERR PREDICT	LOWER95% MEAN	UPPER95% MEAN	LOWER95% PREDICT	UPPER95% PREDICT	RESIDUAL	STD ERR RESIDUAL
1	34.0000	1.5532	21.1775	-89.5673	92.6737	-187.2	190.3	32.4468	32.0646
2	31.0000	29.9069	38.2745	-134.8	194.6	-203.5	263.1	1.0931	3.4190
3	147.0	127.9	35.8143	-26.1944	282.0	-98.1123	353.9	19.0962	13.9269
4	27.0000	39.6496	36.0008	-115.3	194.6	-186.9	266.2	-12.6496	13.4376
5	53.0000	68.0432	36.8887	-90.6776	226.8	-161.1	297.2	-15.0432	10.7634
6	0	31.5666	30.5909	-100.1	163.2	-179.8	242.9	-31.5666	23.2556
7	12.0000	-0.3219	24.3804	-105.2	104.6	-196.1	195.5	12.3219	29.7022

OBS	STUDENT RESIDUAL	-2-1-0 1 2	COOK'S D
1	1.0119	|**	0.089
2	0.3197	|	0.562
3	1.3712	|**	2.487
4	-0.9414	*|	1.272
5	-1.3976	**|	4.589
6	-1.3574	**|	0.638
7	0.4148	|	0.023

SUM OF RESIDUALS	5.698523
SUM OF SQUARED RESIDUALS	2953.246
PREDICTED RESID SS (PRESS)	97693.21

Appendix F.   Regression Equation Analysis.   111