Using In-Process Testing Metrics to Estimate Post-Release Field Quality of Java Programs

Nachiappan Nagappan[1], Laurie Williams[2], Mladen Vouk[3], Jason Osborne[4]

Abstract

In industrial practice, information on the software field quality of a product is available too late in the software lifecycle to guide affordable corrective action. An important step towards remediation of this problem lies in the ability to provide an early estimation of post-release field quality. This paper presents a suite of nine static in-process unit test metrics, the Software Testing and Reliability Early Warning for Java (STREW-J) metric suite. The STREW-J metrics can be used to leverage the software testing effort to predict post-release field quality early and throughout the software development phases. The metric suite is applicable for software products implemented in Java for which an extensive suite of automated unit test cases are incrementally created as development proceeds. We built and validated a prediction model using the STREW-J metrics via a three-phase case study approach which progressively involved 22 small-scale academic projects, 27 medium-sized open source projects, and five industrial projects. The ability of the STREW-J metric suite to estimate post-release field quality via a statistical regression model was evaluated in the three different environments. The error in estimation and the sensitivity of the predictions indicate the STREW-J metric suite can be used effectively to predict post-release software field quality.

Keywords: Software Measurement, Statistical Modeling, Complexity measures, Performance measures, Object oriented systems, Process metrics, Product metrics, Software science.

1 INTRODUCTION

In industry, estimates of software field quality are often available too late in the software lifecycle to guide affordable corrective action to the quality of the software. Field quality cannot be measured before a product has been completed and delivered to an internal or external customer. Because this information is available late in the software lifecycle, corrective actions tend to be expensive (Boehm 1981). Software developers can benefit from an early warning regarding the quality of their product.

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In our research, we formulate this early warning from a collection of static automated unit test metrics that are correlated with Trouble Reports (TRs) per thousand lines of code (KLOC), an external measure of quality obtained from users. A TR (Mohagheghi 2004) is a customer-reported problem whereby the software system does not behave as the customer expects. An internal metric, such as cylomatic complexity (McCabe 1976), is a measure derived from the product itself (ISO/IEC 1996). An external measure is a measure of a product derived from the external assessment of the behavior of the system (ISO/IEC 1996). For example, the number of failures found in test is an external measure.

The ISO/IEC standard (ISO/IEC 1996) states that an internal metric is of little value unless there is evidence that it is related to an externally-visible attribute. Internal metrics have been shown to be useful as early indicators of externally-visible product quality (IEEE 1990) when they are related in a statistically significant and stable way to the field quality/reliability of the product. The validation of internal metrics requires a convincing demonstration that (1) the metric measures what it purports to measure and (2) the metric is associated with an important external metric, such as field reliability, maintainability, or fault-proneness (El Emam 2000).

Our research objective is to construct and validate a set of easy-to-measure, in-process, internal, static unit test metrics that can be used as an early indication of the external measure post-release field quality. To this end, we have created a metric suite we call the Software Testing and Reliability Early Warning for Java (STREW-J) metric suite (Nagappan 2005a). As will be discussed, the metric suite is applicable for software products implemented in Java for which an extensive suite of automated unit test cases are incrementally created as development proceeds. Metrics about these automated unit tests are used to predict post-release field quality and to provide an indication of whether the composition of the unit test cases is adequate to yield a high quality product based upon past results. The STREW-J metrics are used to build a regression model to estimate the post-release field quality in terms of the metric TRs/KLOC.

Figure 1 illustrates how the STREW-J metric suite fits into the tight iterative feedback loop of teams that employ automated testing processes, such as is done with the test-driven development (TDD) (Beck 2003) practice. Via TDD, the incremental creation of the unit tests and the constant re-running of unit tests provides developers with confidence in their implementation; the integration of STREW-J feedback provides guidance on the eternal question, "Have I tested enough?"

Teams develop a history of the value of the STREW-J metrics from comparable projects with acceptable levels of field quality. These historical metric values are then used to estimate the relationship between the STREW-J metric elements and the TRs/KLOC. This early estimate helps to identify areas that require more testing, based on the estimates of post-release field quality.

In this paper, we present empirical results of an academic feasibility study (22 projects), a case study of open source projects (27 projects), and an industrial case study (five projects) which were used to build and validate the STREW-J model as a means of estimating post-release field quality. The remainder of this paper is organized as follows. Section 2 discusses the related work. Section 3 presents the STREW-J metric suite. Section 4 discusses the case studies, and Section 5 presents the conclusions.

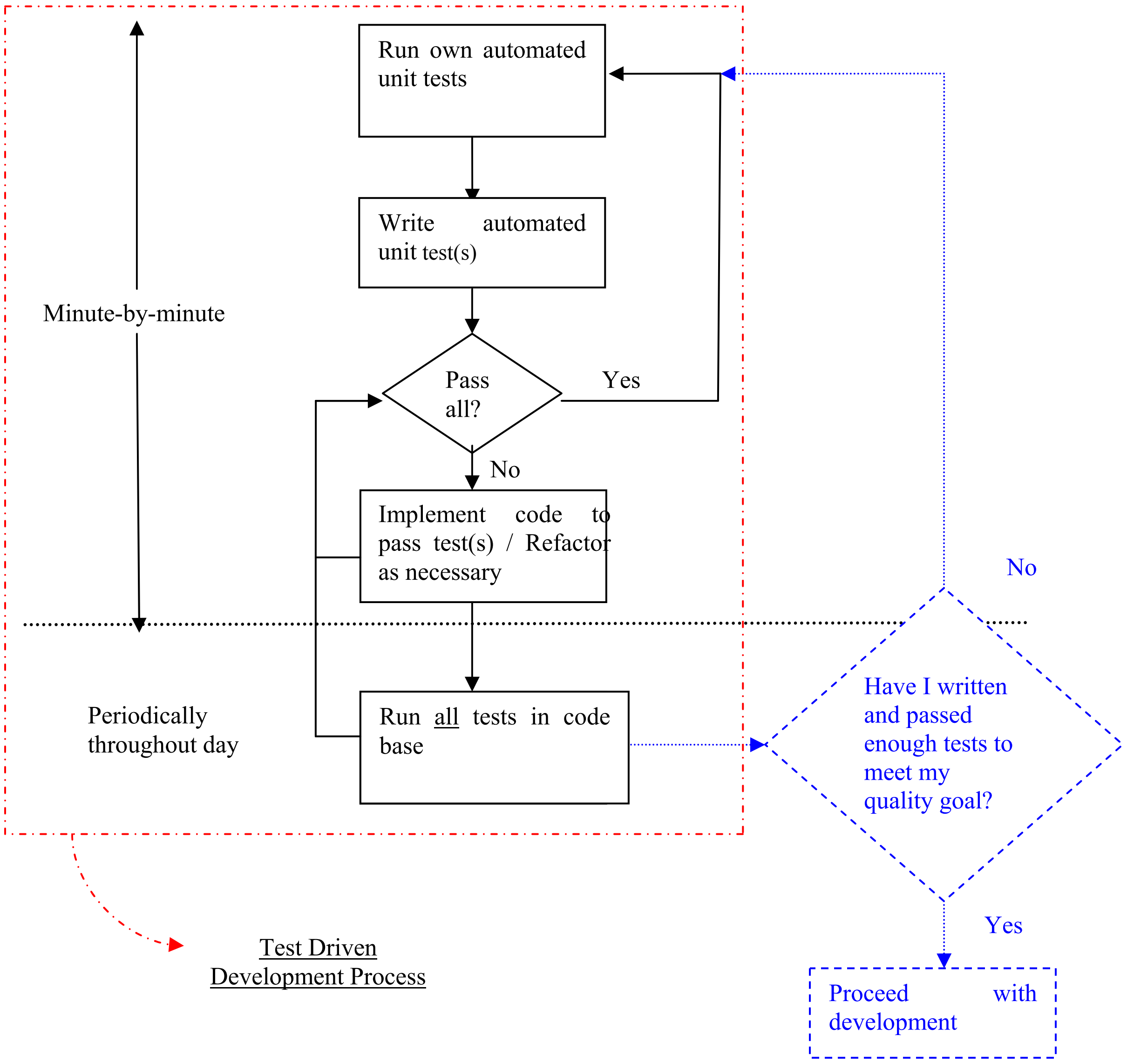

Run own automated unit tests
Write automated unit test(s)
Minute-by-minute
Pass all?
Yes
No
Implement code to pass test(s) / Refactor as necessary
Periodically throughout day
Run all tests in code base
No
Have I written and passed enough tests to meet my quality goal?
Yes
Proceed with development
Test Driven Development Process

Figure 1: STREW-J metric suite process model

2 RELATED WORK

Research shows that internal metrics can be related to external measures of field quality, such as fault-proneness. Software fault-proneness is defined as the probability of the presence of faults in the software (Denaro 2002a). Research on fault-proneness has focused on two areas: (1) the definition of metrics to capture software complexity and testing thoroughness; and (2) the identification of and experimentation with models that relate software metrics to fault-proneness (Denaro 2002a). Structural object-orientation (O-O) measurements, such as those in the Chidamber-Kemerer (C-K) O-O metric suite (Chidamber 1994), have been used to evaluate and predict fault-proneness (Basili, Briand et al. 1996; Briand, Wust et al. 1998; Briand, Wuest et al. 2000). The CK metric suite consists of six metrics: weighted methods per class (WMC), coupling between objects (CBO), depth of inheritance tree (DIT), number of children (NOC), response for a class (RFC) and lack of cohesion among methods (LCOM). These metrics have been shown to be useful early internal indicators of externally-visible product quality in terms of fault-proneness (Basili, Briand et al. 1996; Subramanyam and Krishnan 2003).

Basili et al. (Basili, Briand et al. 1996) studied the fault-proneness in software programs using eight student projects. They observed that the WMC, CBO, DIT, NOC and RFC were correlated with defects while the LCOM was not correlated with defects. Further, Briand et al. (Briand, Wust et al. 1998) performed an industrial case study and observed the CBO, RFC, and LCOM to be associated with the fault-proneness of a class. A similar study done by Briand et al. (Briand, Wuest et al. 2000) on eight student projects showed that classes with a higher WMC, CBO, DIT and RFC were more fault-prone while classes with a higher NOC were less fault-prone. Tang et al. (Tang 1999) studied three real time systems for testing and maintenance defects. Higher WMC and RFC were found to be associated with fault-proneness. El Emam et al. (El Emam, Benlarbi et al. 1999) studied the effect of class size on fault-proneness by using a large telecommunications application. Class size was found to confound the effect of all the metrics on fault-proneness. Finally, Chidamber et al. (Chidamber, Darcy et al. 1998) analyzed project productivity, rework, and design effort of three financial services applications. High CBO and low LCOM were associated with lower productivity, greater rework, and greater design effort.

Vouk and Tai (Vouk 1993) showed that in-process metrics have strong correlation with field quality of industrial software products. They demonstrated the use of software metric estimators, such as the number of failures, failure intensity (indicated by failures per test case), and drivers such as change level measured by lines of code, component usage, and effort to:

1. quantify component quality in terms of the number of failures expected during initial operational deployment;
2. identify fault-prone and failure-prone components; and
3. guide the software testing process to minimize the number of failures/faults that can be expected in future phases.

To summarize, there is a growing body of empirical evidence that supports the theoretical validity of the use of these internal metrics as predictors of fault-proneness. The consistency of these findings varies with the programming language (Subramanyam and Krishnan 2003). Therefore, the metrics are still open to debate (Churcher and Shepperd 1995). The STREW-J will be used to predict the external measure of field quality.

3 STREW-J METRIC SUITE

The STREW-J metric suite consists of internal, in-process unit test metrics that are leveraged to estimate post-release field quality with an associated confidence interval. Section 3.1 discusses the applicability of the STREW-J metric suite, and Section 3.2 the STREW-J metric suite elements.

3.1 Applicability

The use of the STREW-J metrics is predicated on the existence of an extensive suite of automated unit test cases being created as development proceeds. These automated unit tests need to be structured as is done with the one of the object-oriented (O-O) xUnit[5] testing frameworks, such as JUnit[6]. The STREW-J method is not applicable for script-based automated testing because, as will be discussed, the metrics are primarily based upon the O-O programming paradigm. When these xUnit frameworks are used with O-O programming, both test code and implementation code hierarchies emerge.

Figure 2 presents a simplistic example of a parallel structure between a source and test class. For each implementation source code class (e.g. `computation`), there exists a corresponding test code class (e.g. `computationTest`). Often each method/function in an implementation source code class (e.g. `addi`) will have one or more corresponding test code method(s)/functions(s) (e.g. `testaddi`). In industrial practice, often such perfect parallel class structure and one-to-one method/function correspondence is not observed; our example is overly simplistic for illustrative purposes. However, a test hierarchy which ultimately inherits from the TestCase class (in JUnit) is created to exercise the implementation code.

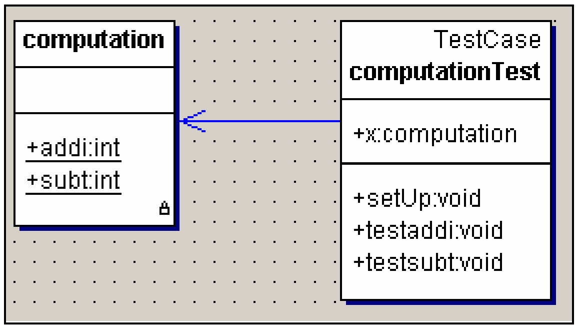


Figure 2: Corresponding source and test classes

Table 1 provides sample Java code for a computation class which adds and subtracts two integers. Notice the `assertEquals` keyword in the `testaddi` and `testsubt` methods. xUnit testing is assert-based. The number of asserts (Rosenblum 1995) and other metrics specific to xUnit-like test automation are used in the STREW-J metric suite.

[5] http://xprogramming.com/software.htm

[6] http://junit.org/

Table 1: Corresponding source and test code

```
   public class computation
   {
      public static int addi(int temp1,int temp2) {
            int temp3
            temp3 = temp1 + temp2;
            return(temp3);
      }
      public static int subt(int temp1,int temp2) {
            int temp3
            temp3 = temp1 - temp2;
            return(temp3);
      }
   }
```

```
  public class computationTest extends TestCase
   {
         public computation x;
         public void setUp() {
                 x=new computation();
         }
         public void testaddi() {
                 assertEquals(100,x.addi(75,25));
         }
         public void testsubt() {
                 assertEquals(40,x.subt(50,10));
         }
   }
```

3.2 STREW-J Metric Suite Elements

The STREW-J Version 2.0 metric suite consists of nine constituent metric ratios. The metrics are intended to cross-check each other and to triangulate upon an estimate of post-release field quality. Each metric makes an individual contribution toward estimation of the post-release field quality but work best when used together. Development teams record the values of these nine metrics and the actual TRs/KLOC of projects. The historical values from prior projects are used to build a regression model that is used to estimate the TRs/KLOC of the current project under development.

The nine constituent STREW-J metrics (SM1 – SM9) and instructions for data collection and computation are shown in Table 2. The nine metrics are static unit test metrics and do not include dynamic metrics, such as code coverage. The metrics can be categorized into three groups: test quantification metrics, complexity and O-O metrics, and a size adjustment metric.

Table 2: STREW-J metrics and collection and computation instructions

Test quantification		
Metric	***ID***	***Description***
$\frac{\textit{Number of Assertions}}{\textit{SLOC}^{*}}$	SM1	Count the number of assertions in all test cases for all source files.
$\frac{\textit{Number of Test Cases}}{\textit{SLOC}^{*}}$	SM2	Count the number of test cases to test all source files.
$\frac{\textit{Number of Assertions}}{\textit{Number of Test Cases}}$	SM3	Count the number of assertions in all test cases for all source files. Count the number of test cases to test all source files.
$\frac{(\textit{TLOC}^{+}/\textit{SLOC}^{*})}{(\textit{Number of Classes}_{Test} / \textit{Number of Classes}_{Source})}$	SM4	Count the number of classes for all source files. Count the number of classes for all test files.
Complexity and O-O metrics		
$\frac{\Sigma\ \textit{Cyclomatic Complexity}_{Test}}{\Sigma\ \textit{Cyclomatic Complexity}_{Source}}$	SM5	Compute the sum of the cyclomatic complexity of all the test files. Compute the sum of the cyclomatic complexity of all the source files.
$\frac{\Sigma\ \textit{CBO}_{Test}}{\Sigma\ \textit{CBO}_{Source}}$	SM6	Compute the sum of the CBO of all the test files. Compute the sum the CBO of all the source files.
$\frac{\Sigma\ \textit{DIT}_{Test}}{\Sigma\ \textit{DIT}_{Source}}$	SM7	Compute the sum of the DIT of each file for all the test files. Compute the sum of the DIT of each file for all the source files.
$\frac{\Sigma\ \text{WMC}_{Test}}{\Sigma\ \text{WMC}_{Source}}$	SM8	Sum the WMC in each file for all the test files. Sum the WMC in each file for all the source files.
Size adjustment		
$\frac{\textit{SLOC}^{*}}{\textit{Minimum SLOC}^{*}}$	SM9	Divide the SLOC* of by the SLOC of the smallest project used to build the STREW.
* *Source Lines of Code (SLOC) is computed as non-blank, non-comment source lines of code* $^{+}$ *Test Lines of Code (TLOC) is computed as non-blank, non-comment test lines of code*		

The **test quantification metrics** (SM1, SM2, SM3, and SM4) are specifically intended to crosscheck each other to account for coding/testing styles. For example, one developer might write fewer test cases, each with multiple asserts checking various conditions. Another developer might test the same conditions by writing many more test cases, each with only one assert. We intend for our metric suite to provide useful guidance to each of these developers without prescribing the style of writing the test cases. Assertions are used in two of the metrics as a means for demonstrating that the program is behaving as expected and as an indication of how thoroughly the source classes have been tested on a per class level. SM4 serves as a control measure to counter the confounding effect of class size, as shown by El-Emam (El Emam, Benlarbi et al. 1999), on the prediction efficiency.

The **complexity and O-O metrics** (SM5, SM6, SM7, and SM8) examine the relative ratio of test to source code for control flow complexity and for a subset of the CK metrics. The dual hierarchy of the test and source code allows us to collect and relate these metrics for both test and source code. These relative ratios for a product under development can be compared with the historical values from prior comparable projects to indicate the relative complexity of the testing effort with respect to the source code. The metrics are now discussed more fully:

- The *cyclomatic complexity* (McCabe 1976) metric for software systems is adapted from the classical graph theoretical cyclomatic number and can be defined as the number of linearly independent paths in a program. Prior studies have found a strong correlation between the cyclomatic complexity measure and the number of test defects (Troster 1992). Studies have also shown that code complexity correlates strongly with program size measured by lines of code (Kan 2003) and is an indication of the extent to which control flow is used. The use of conditional statements increases the amount of testing required because there are more logic and data flow paths to be verified (Khoshgoftaar and Munson 1990).

- The larger the inter-object *coupling (CBO)*, the higher the sensitivity to change (Chidamber 1994). Therefore, maintenance of the code is more difficult (Chidamber 1994). Prior studies have shown coupling to be related to fault-proneness (Basili, Briand et al. 1996; Briand, Wust et al. 1998; Briand, Wuest et al. 2000). As a result, the higher the inter-object class coupling, the more rigorous the testing should be (Chidamber 1994).
- A higher depth of inheritance (*DIT)* indicates desirable reuse but adds to the complexity of the code because a change or a failure in a super class propagates down the inheritance tree. DIT and fault-proneness were shown to be strongly correlated (Basili, Briand et al. 1996; Briand, Wuest et al. 2000).
- The *number of methods* and the *complexity of methods* is a predictor of how much time and effort is required to develop and maintain the class (Chidamber 1994). The larger the number of methods in a class, the greater is the potential impact on children, since the children will inherit all the methods defined in the class. The ratio of the WMC_{test} and WMC_{source} measures the relative ratio of the number of test methods to source methods. This measure serves to compare the testing effort on a method basis. The relationship between the WMC as an indicator of fault-proneness has been demonstrated in prior studies (Basili, Briand et al. 1996; Briand, Wust et al. 1998).

The final metric is a **relative size adjustment factor (RSAF)**. Defect density has been shown to increase with class size (El Emam, Benlarbi et al. 1999). We account for project size in terms of SLOC for the projects used to build the STREW-J prediction equation using RSAF.

The metrics that comprise the STREW-J metric suite have evolved (Nagappan, Williams et al. 2003; Nagappan 2004) through our case studies. Some metrics were removed based on the lack of their ability to contribute to the estimation of post-release field quality and due to pre-existing inter-correlations between the elements. These metrics were removed based upon statistical inter-correlations, multicollinearity, stepwise, backward, and forward regression techniques (Kleinbaum 1987) of case study data. The following metrics were removed:

- Number of requirements/Source lines of code
- Number of children_{test}/Number of children_{source}
- Lack of cohesion among methods_{test}/Lack of cohesion among methods_{source}

4 STREW-J MODEL BUILDING AND VALIDATION

This section discusses the three-phase of case studies used to build and validate the use of the STREW-J metric suite for estimating post-release field quality. The validation studies are performed in three different environments to build an empirical body of knowledge. Drawing general conclusions from empirical studies in software engineering is difficult because any process depends to a large degree on a potentially large number of relevant context variables.

For this reason, we cannot assume *a priori* that the results of a study generalize beyond the specific environment in which it was conducted (Basili, Shull et al. 1999). Researchers become more confident in a theory when similar findings emerge in different contexts (Basili, Shull et al. 1999). By performing multiple case studies and/or experiments and recording the context variables of each case study, researchers can build up knowledge through a family of experiments (Basili, Shull et al. 1999) which examine the efficacy of a new practice. Replication of experiments addresses threats to experimental validity. We address these issues related to empirical studies by replicating multiple case studies through a family of experiments in three different contexts: academic, open source and industrial. Similar results in these contexts indicate the promise of this approach at statistically significant levels.

4.1 Model Building

This section describes the model building strategies that were used for predicting post-release field quality. A number of techniques have been used for the analysis of software quality. Multiple linear regression (MLR) analysis (Khoshgoftaar 1993) has been used to model the relationship between quality and software metrics. The general regression equation is of the form:

$$Y = c + a_1X1+a_2X2+.....+a_nXn, \tag{1}$$

where Y is the dependent variable, a_1, a_2 …., a_n are regression coefficients and X1, X2 …., Xn are the known independent variables.

In our work, the dependent variable to be estimated is the post-release field quality and the independent variables are the STREW-J metrics.

A difficulty associated with MLR is multicollinearity among the metrics that can lead to inflated variance in the estimation of reliability. One approach that has been used to overcome this difficulty is Principal Component Analysis (PCA) (Jackson 2003). With PCA, a smaller number of uncorrelated linear combinations of metrics that account for as much sample variance as possible are selected for use in regression (linear or logistic). A logistic regression equation (Denaro 2002b) can be built to model data using the principal components as the independent or predictor variables. Denaro et al. (Denaro 2002b) calculated 38 different software metrics for the open source Apache 1.3 and 2.0 projects. Using PCA, they selected a subset of nine of these metrics that explained 95% of the total sample variance.

As will be discussed, in our case studies the nine STREW-J metrics demonstrated multicollinearity, and therefore PCA was used to reduce the STREW-J metrics that are highly correlated with other metrics to a smaller number of uncorrelated linear combinations of these metrics. The Kaiser-Meyer-Olkin (KMO) (Kaiser 1974) test of sampling adequacy was used to identify multicollinearity, indicating the applicability of using the principal components produced by PCA, rather than the nine individual metrics, in an MLR equation. For PCA to be applicable, the KMO measure of sampling adequacy should be greater than 0.6 (Brace 2003). The KMO measure of sampling adequacy is a test of the amount of variance within the data that can be explained by the measures. Therefore, throughout the rest of this paper we present the results using PCA. A comparative analysis of the results of this research obtained using MLR and PCA is available (Nagappan 2005a). PCA generates uncorrelated linear combinations of attributes, overcoming the variance inflation in estimating post-release field quality caused by multicollinearity. Multiple regression analysis is performed on the principal components produced. The generalized regression equation and associated confidence are formulated as follows:

$$Y_{new} = c + a_1PC1+a_2PC2+.....+a_nPCn, \tag{2}$$

where a_1, a_2 …., a_n are regression coefficients and PC1, PC2 …., PCn are the produced principal components.

The estimated value of post-release field quality (Y_{new}) is calculated with an associated confidence bound (Kleinbaum 1987) given by Equation 3 where n is the number of observations, $t_{(\alpha/2,\ n)}$ is the standard t-table value with n degrees of freedom at a significance level of $\alpha = 0.05$.

$$\textit{Confidence bounds} = Y_{new} \pm t_{(\alpha/2,\ n)} * \textit{Mean Standard Error} \tag{3}$$

Further, the model building strategies have the following associated factors:

- The coefficient of determination, R^2, is the ratio of the regression sum of squares to the total sum of squares. As a ratio, it takes values between 0 and 1, with larger values indicating more variability explained by the model and less unexplained variation.
- The F-ratio is to test the null hypothesis that all regression coefficients are zero at statistically significant levels.
- Where parametric testing is appropriate, a significance level of $\alpha = 0.05$ was adopted for statistical inference. For example, all interval estimates are reported using confidence level 95% ($\alpha = 0.05$).

4.2 Results Evaluation Techniques

The evaluation of the TRs/KLOC estimates with the actual values is performed using two methods explained below:

- *Average Absolute Error (AAE) and Average Relative Error (ARE).* AAE and ARE are used to measure the accuracy of prediction of the estimated TRs/KLOC with numerical quantification (i.e. numerical accuracy) (Khoshgoftaar 2003). The smaller the values of AAE and ARE, the better are the predictions. The equations for AAE and ARE are provided as Equations 4 and 5 where n is the number of observations.

$$AAE = \frac{1}{n}\sum_{i=1}^{n} |\ \textit{Estimated Value} - \textit{Actual Value}\ | \tag{4}$$

$$ARE = \frac{1}{n}\sum_{i=1}^{n} (|\ \textit{Estimated Value} - \textit{Actual Value}\ |) / \textit{Actual Value} \tag{5}$$

- *Correlation between the actual and estimated TRs/KLOC.* This correlation is used to quantify the sensitivity of prediction. The two correlation techniques utilized are (1) the Spearman rank correlation which is a commonly-used robust rank correlation technique because it can be applied when the association between elements is non-linear; and (2) the Pearson bivariate correlation is best suited for normally distributed data and where the association between elements is linear (Fenton and Pfleeger 1998). A positive relationship between the actual and estimated values is desired in terms of the more robust Spearman rank correlation.

A positive correlation between the actual and estimated TRs/KLOC would indicate that with an increase in estimated TRs/KLOC, there is an increase in actual TRs/KLOC. A negative correlation would indicate that with an increase in estimated TRs/KLOC, there is a decrease in actual TRs/KLOC (or vice versa).

4.3 Case Studies

This section describes the three-phase empirical case study approach used to build the STREW-J model and to validate the effectiveness of the model. The three phases include case studies of 22 academic projects, 27 open source projects, and five industrial projects. For our case studies, the TRs were screened to remove duplicates and reports due to documentation problems. The data used for the academic and open source projects are publicly available in (Nagappan 2005a).

4.3.1 Feasibility study: Academic projects

This subsection describes a controlled feasibility study performed with junior/senior-level students at North Carolina State University (NCSU) to investigate the efficacy of the STREW-J metric suite elements to estimate post-release field quality.

4.3.1.1 Description

The students worked on a project that involved development of an Eclipse[7] plug-in to collect software metrics. The project was six weeks in duration and used Java as the programming language. The JUnit testing framework was used for unit testing; students were required to have 80% statement coverage. A total of 22 projects were submitted, and each group had four to five students. Figure 3 shows the size (LOC_{source}) in lines of code (LOC) of the projects that were developed. The projects were between 617 LOC_{source} and 3,631 LOC_{source}. On average, the ratio of LOC_{test} to LOC_{source} was 0.35. Each project was evaluated by 45 independent test cases. Post-release field quality was estimated by instructor-run black box test case failures per KLOC because the student projects were not released to customers. If a 2 KLOC project had ten failures (out of the 45 tests) the TRs/KLOC = (10/2) = 5 failures/KLOC.

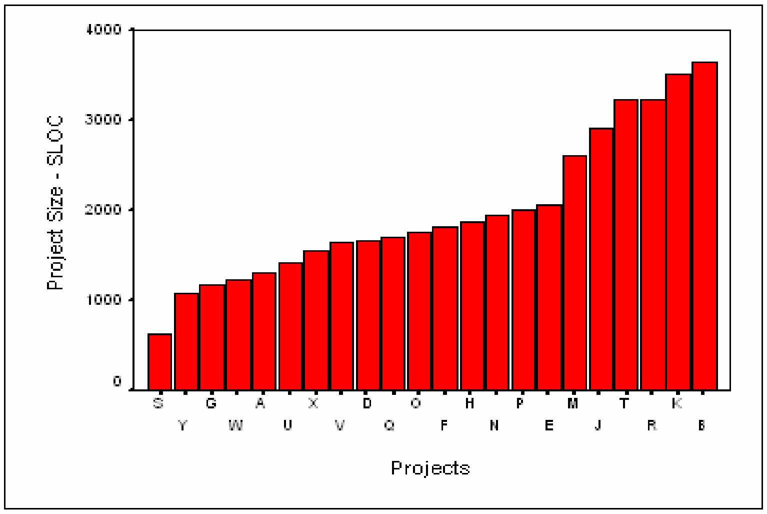


Figure 3: Academic projects size

[7] http://eclipse.org/

4.3.1.2 Limitations

The academic study is a closed structured environment that might represent ideal conditions but may not reflect industrial settings. As a result, an external validity issue arises because the programs were written by students, and the projects are small relative to industry applications. This concern is mitigated to some degree because the students were advanced undergraduates (junior/senior). Another threat to validity is that using the same set of 45 test cases to evaluate post-release field quality may also have skewed the failures/KLOC to a certain degree. It is possible that under exhaustive usage by customers a project with higher 'test' failures/KLOC would actually have fewer customer-realized failures.

4.3.1.3 Model building

The regression model was built using the principal components obtained from the STREW-J metrics as the independent variables and the post-release field quality as the dependent variable for all 22 projects. The built model had an R^2 value = 0.512 and was statistically significant (F=6.284, p=0.004).

4.3.1.4 Random data splitting

To evaluate the efficacy of the STREW-J metric suite to predict TRs/KLOC, we use a random data splitting approach. We randomly selected two-thirds (N=15) of the samples to build a prediction model and the remaining one-third (N=7) to evaluate the built model. We obtained the results shown in Table 3.

Table 3: Prediction evaluation results

	PCA
Model Fit (15 projects)	R^2= 0.598, (F=5.463, p=0.015)
Prediction Evaluation (7 projects)	AAE=4.47, ARE=1.27 Pearson correlation = 0.328 (p=0.473) Spearman correlation = 0.464 (p=0.294)

The AAE and ARE results in Table 3 indicate that the model produces an estimate that is indicative of the true TRs/KLOC. The ARE and AAE values are less than the standard deviation of the TRs/KLOC (standard deviation is 7.74 TRs/KLOC). The actual values of TRs/KLOC range from 1.43 TRs/KLOC to 35.5 TRs/KLOC indicating a wide spectrum of quality in terms of TRs for the academic projects. This range of TRs/KLOC of the projects is shown by the histogram in Figure 4. In spite of the wide spectrum of the TRs/KLOC, the ARE and AAE values indicate the feasibility of using the STREW-J metric suite compared to the actual values of the TRs/KLOC. The Pearson and Spearman rank correlation is not statistically significant. The reason for the correlation coefficients to be positive but not statistically significant might be due to the small sample size (seven projects). A repeated random splitting yielded similar results (Nagappan 2005b). The results of this feasibility study motivated further investigation using open source and industrial projects to investigate the utility of the STREW-J metric suite to predict TRs/KLOC on larger scale projects.

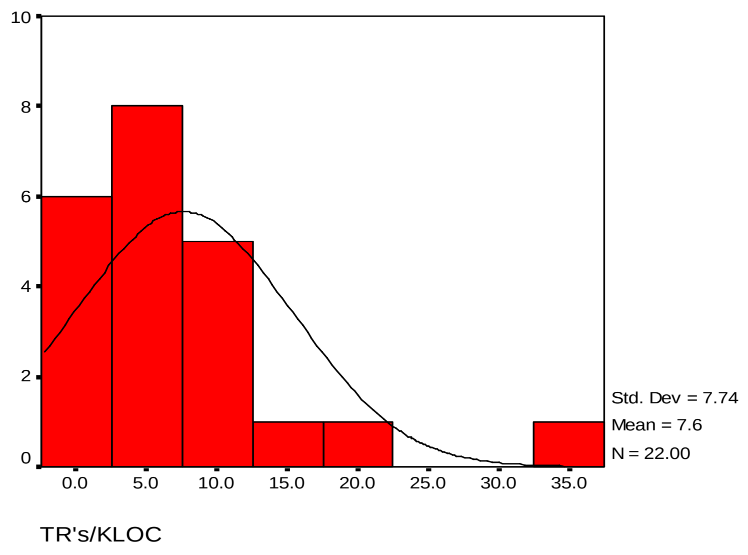


Figure 4: Histogram of TRs/KLOC in academic projects

4.3.2 Open source case studies

Open source projects are convenient to perform post-release field quality analysis because source code, test code, and defect logs are openly available for use. Additionally, these projects are more representative of industrial projects than academic projects due to their size and scope. We selected 27 open source projects to apply the STREW-J metric suite.

4.3.2.1 Description

Twenty-seven open source projects that were developed in Java were selected from Sourceforge (http://sourceforge.net). The following criterion was used to select the projects from Sourceforge.

- *software development tools*. All of the chosen projects are software development tools, i.e. tools that are used to build and test software and to detect defects in software systems to select programs from a common domain.
- *download ranking of 85% or higher.* In Sourceforge, the projects are all ranked based on the number of times they have been downloaded on a percentile scale from 0-100%. For example, a ranking of 85% means that a product is in the top 15% in terms of download quantity. We chose this criterion because we reasoned that a comparative group of projects with similarly high download rates would be more likely to have a similar usage frequency by customers that would ultimately reflect the post-release field quality.
- *automated unit testing*. The projects needed to have JUnit automated tests.
- *defect logs available*. The defect log needed to be available for identifying TRs with the date of the TR reported.
- *active fixing of TRs*. The TR fixing rate is used to indicate the system is still in use. The time between the reporting of a TR and the developer fixing it serves as a measure of this factor. Projects that had open TRs that were not assigned to anyone over a period of three months were not considered.

- *Sourceforge development stage of 4 or higher*. This denotes the development stage of the project (1-6) where 1 is a planning stage and 6 is a mature phase. We chose a cut-off of 4 which indicates the project is at least a successful beta release. This criterion indicates that the projects are at a similar stage of development and are not projects too early in the development lifecycle.

Figure 5 shows the names of the projects and their sizes in LOC_{source}. On average, the ratio of LOC_{test} to LOC_{source} was 0.37. The projects range from around 2.5 $KLOC_{source}$ to 80 $KLOC_{source}$. The TRs are normally distributed with a range from 0.20 to 6.9 TRs/KLOC (Mean = 1.42). The defect logs were screened, and duplicate TRs were removed to obtain an accurate measure of the TRs/KLOC.

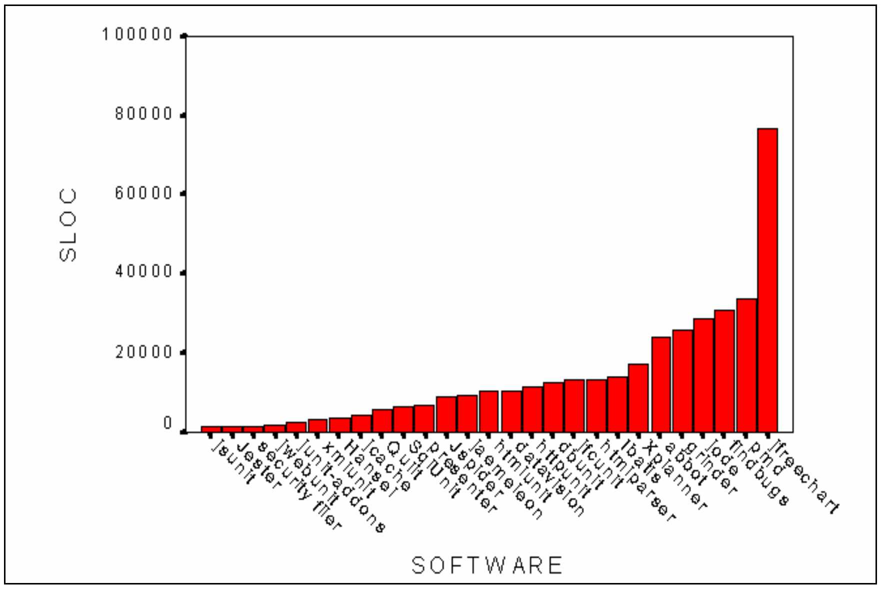


Figure 5: Open source project sizes

4.3.2.2 Limitations

There is a validity issue with respect to the actual usage of open source software systems. The commonly-available usage metric for open source software is the download activity ratio. For example, it might be possible that both Project 1 and Project 2 could have both been downloaded by 100 users, but Project 1 might have been actually used by only ten users while Project 2 by 90 users. Actual usage is not directly observable from the sourceforge.com. Also, we are dependent on customer reports for measuring the TRs/KLOC. However, some customers might not report the TRs in the open source environment.

We assume that the TRs are representative of the operational profile [29] of the software system. If the different components of the software systems were not used equally, the estimation of TRs can be misleading. For example, a different set of customers could use the product for a different purpose and might exercise the product in a different way. This different usage would exercise different parts of the code and could surface a different post-release product quality. The issues of the generalizability of the actual operation profile is negated to some extent by the uniform testing efforts of the projects (using unit testing measured by test lines of code, assertions, and test cases), comparable TRs/KLOC across all the projects, and all the projects belonging to one particular domain of software systems.

4.3.2.3 Model building

Multiple regression was performed using the principal components of the STREW-J metrics for the 27 open source projects as the independent variable and the post-release field quality as the dependent variable. Similar to the academic case studies, the model was statistically significant (R^2=0.428, F=8.993, p=0.004) in its ability to explain the variance in the dependent variable.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.764 indicating the applicability of using PCA in model building. The PCA of the nine STREW-J metrics yields two principal components (with eigen values greater than 1). The linear transformation coefficient for the two principle components is given by the component matrix[8] in Table 4.

Table 4: Component matrix for PCA transformation

	Component	
	PC1	PC2
SM1	.793	.284
SM2	.795	-.281
SM3	-.270	.701
SM4	.935	-6.280E-03
SM5	.159	-.745
SM6	.877	.102
SM7	.699	.457
SM8	.864	4.126E-02
SM9	-.569	.233

Using MLR on the two principal components calculated using Table 4, we obtain Equation 5.

$$\textit{Post-release field quality} = 1.424 + 0.852 * PC1 - 0.132*PC2 \qquad (5)$$

where PC1 and PC2 are the transformed principal components produced from the nine STREW-J metrics.

4.3.2.4 Random data splitting

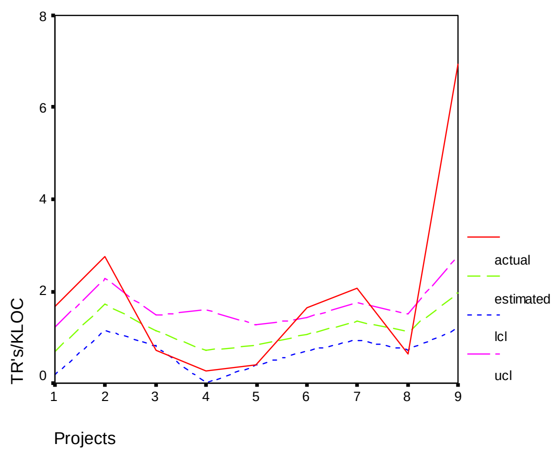
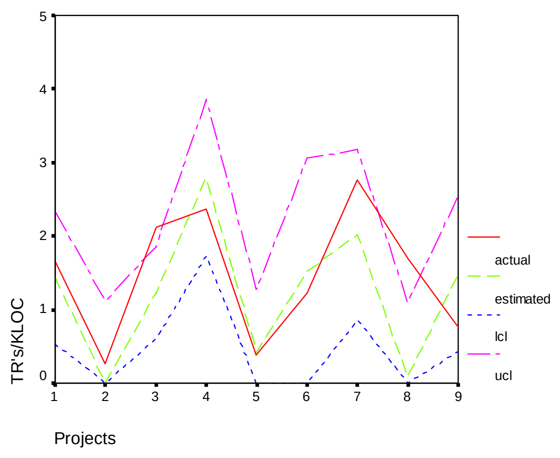
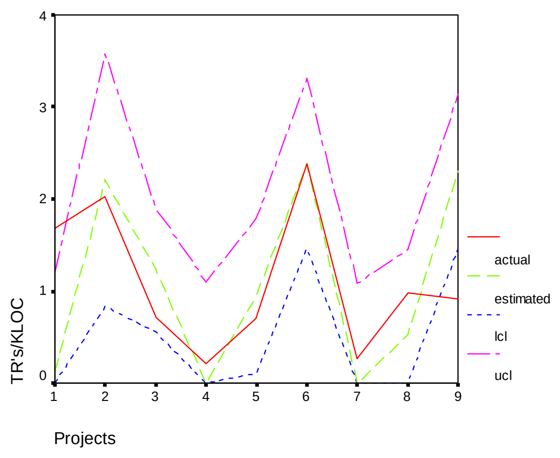
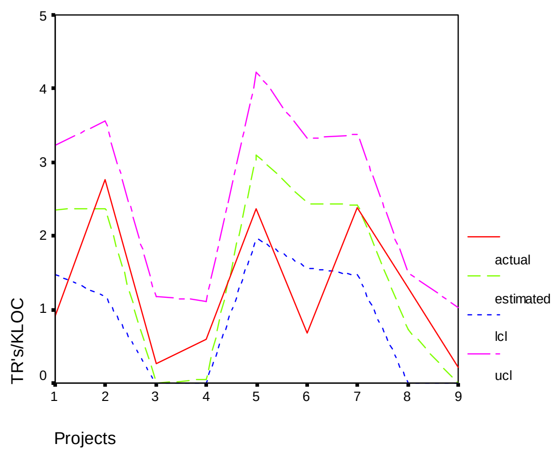
For the random data-splitting, we use two thirds of the projects (N=18) to build the prediction model and the remaining one-third (N=9) to evaluate the fit of the prediction model. We repeated the random split nine times to verify data consistency, i.e. to check if the results of our analysis were not a one-time occurrence. Figure 6 shows the model building and model evaluation performed using PCA. The results for each data split present the R^2 and F test results for each model and the prediction results evaluated using AAE, ARE and correlation analysis. The graphs indicate the actual and the estimated post-release field quality along with the regression predicted upper confidence level (ucl) and lower confidence level (lcl) (Kleinbaum 1987).

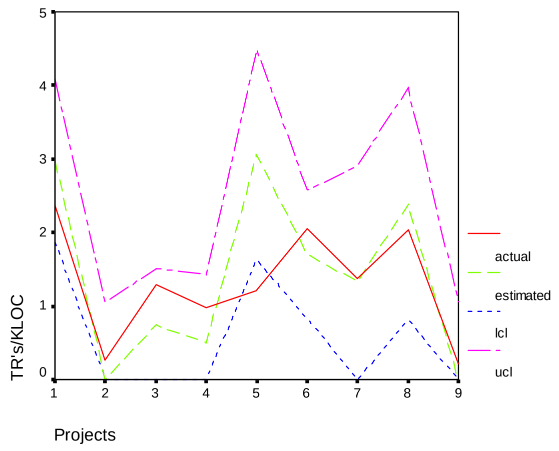
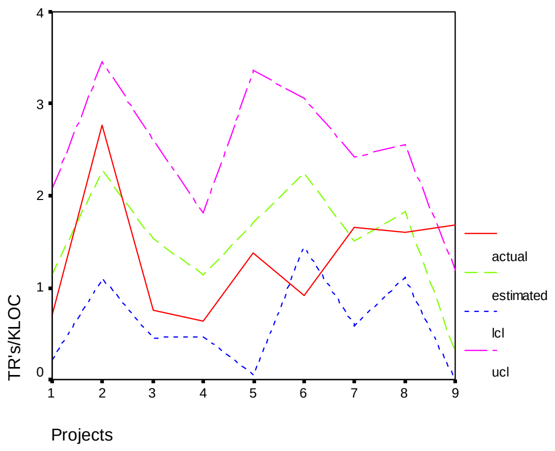
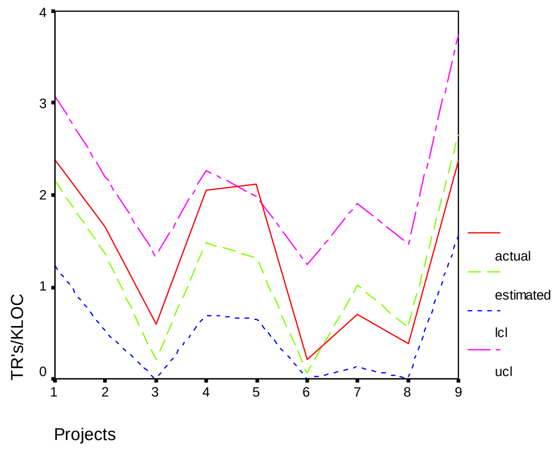
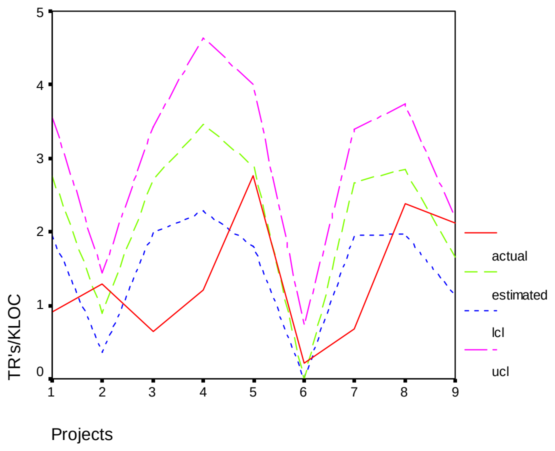
[8] This component matrix for the academic projects feasibility study is available (Nagappan 2005a) .

To summarize, we present the results of our evaluation using the models built using PCA in Table 5. We can assess the efficacy of the prediction model built using 18 randomly-chosen projects. The ARE values that reflect the relative error in terms of the absolute magnitude of the TRs/KLOC. The overall standard deviation of the TRs/KLOC is 1.318 TRs/KLOC.

Table 5: AAE and ARE for PCA models

Random Split	AAE	ARE	Pearson (p value)	Spearman (p value)
1.	1.1230	0.3276	0.834 (p=0.005)	**0.700** (p=0.036)
2.	0.6400	0.2796	0.694 (p=0.038)	**0.617** (p=0.077)
3.	0.5600	0.2900	0.641 (p=0.063)	**0.667** (p=0.050)
4.	0.7322	0.4034	0.732 (p=0.025)	**0.700** (p=0.036)
5.	0.5533	0.2599	0.799 (p=0.010)	**0.717** (p=0.030)
6.	0.6200	0.2900	0.279 (p=0.467)	0.317 (p=0.406)
7.	0.3555	0.1525	0.905 (p=0.001)	**0.917** (p=0.001)
8.	1.1011	0.574	0.351 (p=0.354)	0.467 (p=0.205)
9.	0.4922	0.2493	0.721 (p=0.028)	**0.667** (p=0.050)

PCA – Random split 1	**PCA – Random split 2**
R^2= 0.373 (F=4.467, (p=0.030))	R^2= 0.442 (F=5.938, p=0.013)
	
AAE = 1.1230, ARE = 0.3276 Pearson correlation = 0.834 (p=0.005) Spearman correlation = 0.700 (p=0.036)	AAE = 0.6400, ARE = 0.2796 Pearson correlation = 0.694 (p=0.038) Spearman correlation = 0.617 (p=0.077)
PCA – Random split 3	**PCA – Random split 4**
R^2= 0.450, (F=6.136, p=0.011)	R^2= 0.450, (F=6.138, p=0.011)
	
AAE = 0.5600, ARE = 0.2900 Pearson correlation = 0.641 (p=0.063) Spearman correlation = 0.667 (p=0.050)	AAE = 0.7322, ARE = 0.4034 Pearson correlation = 0.732 (p=0.025) Spearman correlation = 0.700 (p=0.036)

PCA – Random split 5	**PCA – Random split 6**
R^2= 0.446, (F=6.038, p=0.012)	R^2= 0.491, (F=7.229, p=0.006)
	
AAE = 0.5533, ARE = 0.2599 Pearson correlation = 0.799 (p=0.010) Spearman correlation = 0.717 (p=0.030)	AAE = 0.6200, ARE = 0.2900 Pearson correlation = 0.279 (p=0.467) Spearman correlation = 0.317 (p=0.406)
PCA – Random split 7	**PCA – Random split 8**
R^2= 0.367, (F=4.355, p=0.032)	R^2= 0.642, (F=13.463, p<0.0005)
	
AAE = 0.3555, ARE = 0.1525 Pearson correlation = 0.905 (p=0.001) Spearman correlation = 0.917 (p=0.001)	AAE = 1.1011, ARE = 0.5740 Pearson correlation = 0.351 (p=0.354) Spearman correlation = 0.467 (p=0.205)

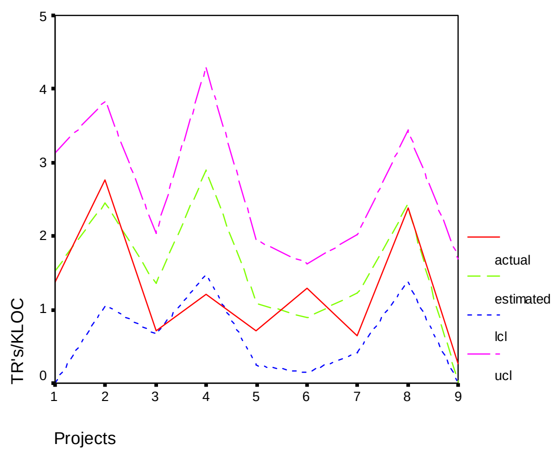
PCA – Random split 9
R^2= 0.435, (F=5.765, p=0.014)

AAE = 0.4922, ARE = 0.2493 Pearson correlation = 0.721 (p=0.028) Spearman correlation = 0.667 (p=0.050)

Figure 6: Random data split – model building and evaluation results

The AAE in all the nine random cases (using PCA after eliminating multicollinearity) is smaller than the standard deviation, indicating that the efficacy of the prediction results.

Table 5 indicates the correlation coefficient (Pearson and Spearman) results between the actual and estimated post-release TRs/KLOC. The correlation measure serves to indicate the sensitivity between the actual and predicted post-release TRs/KLOC. Of nine random samples in the PCA, seven are statistically significant (between the estimated and actual post-release quality), indicating the efficacy of our approach for the open source projects case study (shown in bold in Table 5).

4.3.3 Industrial case study

In this section we describe the industrial case study that was performed with a multinational, travel services company to investigate the efficacy of the STREW-J metric suite to assess post-release field quality for three commercial software systems.

4.3.3.1 Description

Our industrial case study involved three software systems (five versions). To protect proprietary information, we keep the name and nature of the projects anonymous. These projects were critical in nature because failures could lead to loss of essential funds for the company. The project sizes that were used for analysis are shown in Table 6.

Table 6: Industrial project sizes

Project	Size
Project 1A	190 KLOC
Project 1B	193 KLOC
Project 2A	504 KLOC
Project 2B	487 KLOC
Project 3	13 KLOC

The development language used was Java, and the JUnit testing framework was used for unit and acceptance testing. Table 7 represents the descriptive project characteristics of our industrial case studies.

Table 7: Project characteristics

Factor	Team value
Team size	Ranged from 6 to 16 developers.
Team education level	62% had a bachelors degree and 34% had a masters degree or higher.
Experience level of team	57% have more than five years of experience in the industry
Domain expertise	Medium-High.
Language expertise	Medium-High.

4.3.3.2 Limitations

Project 3 was of much smaller size compared to the other projects. Also Project 3 was a new release of a system. But all the three projects belonged to the same domain in terms of functional usage thereby having comparable TR/KLOC values.

4.3.3.3 Post-release field quality prediction

In the industrial environment, failures found by customers are reported back to the organization. These failures are then mapped back to the appropriate software systems. We use Equation 5, built using the principal components of the STREW-J metrics of the open source projects, to predict the post-release field quality of the industrial software systems. Figure 7 indicates the prediction plots obtained using PCA.

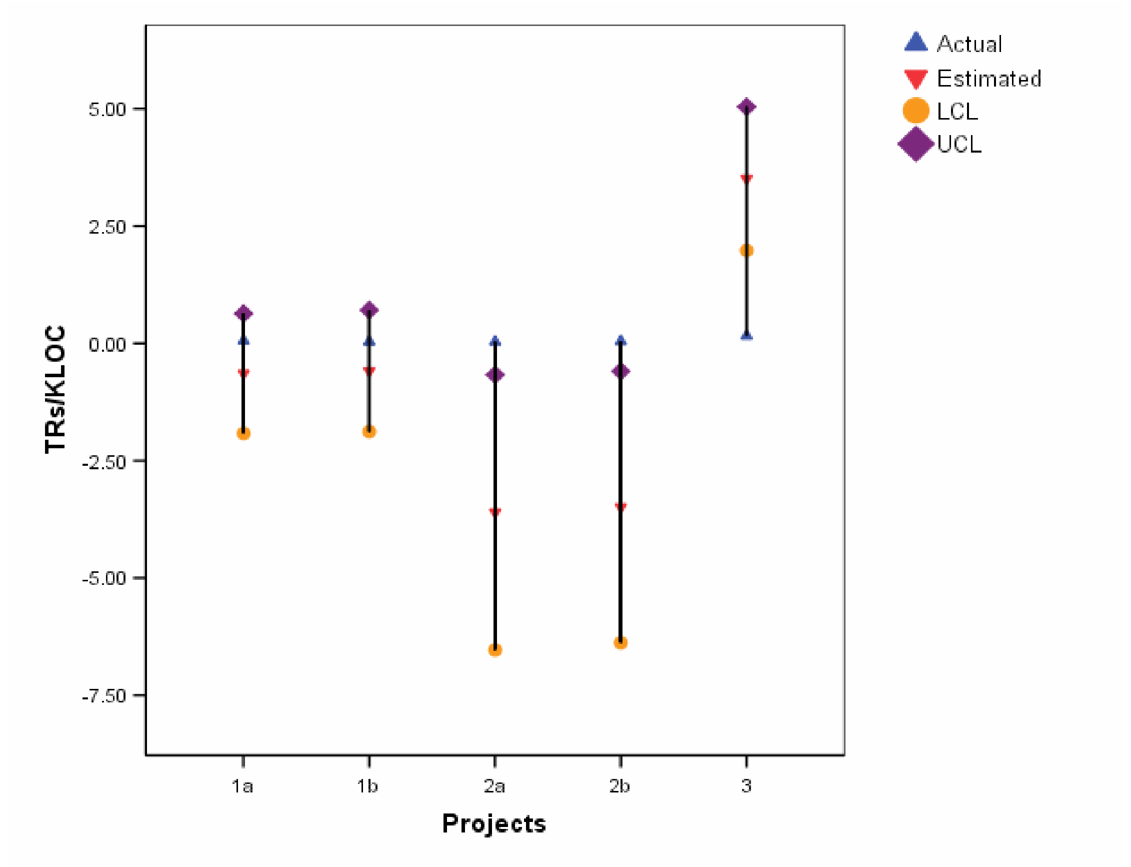


Figure 7: Prediction plots with PCA

Figure 7 indicates the predicted values of the actual TRs/KLOC and bounds for Projects 1A/B, 2A/B and C. The actual normalized TRs/KLOC values are close to the zero for all the projects. The critical nature of the project drives the development organization to focus on practices which yield high quality products. The lower confidence bounds (LCL) are all negative (although it is impossible to actually have a negative TR/KLOC) because the regression equation yields point estimates which appropriately predict a near-perfect project. Project 3 exhibits a variant behavior than the others. Project 3 may not be a comparable project because it is smaller than the other projects and was to form the core components of the organization's future software products. Therefore, Project 3 was particularly well tested, considerably more than the other software systems used to build or evaluate the prediction. On closer observation of the nine STREW-J metric values for Project 3, we notice that metrics SM1, SM2 for Project 3 at least one order greater than all the projects (open source included). Metrics SM5, SM6, SM7, and SM8 for Project 3 are at least twice of SM5, SM6, SM7 and SM8 of all the other projects. SM5-SM8 indicate that Project 3 had a high testing effort (and complexity) compared to all the other projects. These differences prevent the open source model from being as accurate a predictor for Project 3.

In all cases, the upper confidence bounds (UCL) are larger than the actual value. Organizations can take a conservative approach and use the upper bounds of TRs/KLOC to be the actual estimated TRs/KLOC to drive the overall quality higher. Even though the sample size is small (only 5 projects), we present the correlation results of the actual and estimated TRs/KLOC. The Pearson correlation coefficient = 0.962 (p = 0.009) and Spearman correlation coefficient = 0.500 (p = 0.391). This indicates the efficacy of the sensitivity of prediction between the actual and estimated TRs/KLOC, but is limited to a certain degree by the small sample size of the available projects.

5 CONCLUSIONS AND FUTURE WORK

An early estimation of potential software field quality can be useful to developers in predicting the overall quality of the software system. However, in most production environments, field quality is measured too late to affordably guide significant corrective actions. In this paper, we present the use of an in-process suite of static test metrics for providing an early warning regarding post-release field quality based on the thoroughness of a testing effort.

The STREW-J metric suite is intended to be easy to gather in the development environment so that developers can receive an early indication of system TRs/KLOC throughout development. Our results indicate that the STREW-J metric suite can be used to leverage the testing effort to estimate the post-release field quality of the software. The STREW-J metric suite is a set of static unit test measures that can be used to estimate the dynamic measure of post-release field quality. Three case studies in the academic, open source, and industrial environments yielded empirical evidence of the ability of the STREW-J metric suite to predict post-release field quality. The associations between appropriately-chosen functions of the metrics, (by using PCA) and the field quality measures were statistically significant.

The data used to build our models was obtained from a relatively small set of data points and contexts. We will continue as was done with the COCOMO II cost estimation model (Boehm, Abts et al. 2000) by Barry Boehm at USC. Over a period of 19 years, Boehm has collected 161 data points (Boehm, Abts et al. 2000) from commercial, aerospace, government, and nonprofit organizations. We will build a more general, robust STREW-based post-release field quality estimation model by obtaining data from many industrial organizations, in multiple domains, with varying degrees of quality. Similar to the progression of the COCOMO model, we plan to make our model robust to handle projects with a wide spectrum of post-release field quality.

We will continue to validate the metric suite in industrial and academic environments and to refine the metric suite according to specific industry characteristics with emphasis on smaller granularity of measurement, i.e. instead on a project basis, measure the STREW-J metrics on a function/class basis to provide more individual feedback to developers. We will continue to refine the metric suite by adding/deleting new metrics based on the results of further studies. An important step towards generalizing STREW-J would involve modifying STREW-J metrics for non–OO languages, such as C, that form a large part of the legacy code base. We plan to use non-automated test results with STREW-J to further enhance the measurement of the testing effort.

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