Assessing the Applicability of Fault-Proneness Models Across Object-Oriented Software Projects

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ABSTRACT
A number of papers have investigated the relationships between design metrics and the detection of faults in object-oriented software. Several of these studies have shown that such models can be accurate in predicting faulty classes within one particular software product. In practice, however, prediction models are built on certain products to be used on subsequent software development projects. How accurate can these models be considering the inevitable differences that may exist across projects and systems? Organizations typically learn and change. From a more general standpoint, can we obtain any evidence that such models are economically viable tools to focus validation and verification effort? This paper attempts to answer these questions using fault and design data collected on two mid-sized Java systems developed in the same environment. Another contribution of the paper is the use of a novel exploratory analysis technique (MARS) to build such fault-proneness models, whose functional form is a priori unknown.

Results indicate that a model built on one system can be accurately used to rank classes within another system according to their fault-proneness. The downside, however, is that, because of system differences, the predicted fault probabilities are not representative of the system predicted. Furthermore, a cost-benefit model demonstrates that the MARS fault-proneness model is potentially viable, from an economical standpoint. The linear model is not, thus suggesting a more complex model is required.

1 INTRODUCTION

Measures of structural design properties such as coupling or complexity are widely considered to be indicators of external system quality attributes, such as reliability or maintainability. Many measures taking structural properties of object-oriented systems into account were proposed in the literature [1][8][6]. A number of case studies have provided empirical evidence that by using regression analysis techniques, highly accurate prediction models for class fault-proneness can be built from existing OO design measures [4][5]. The accuracy of the prediction models in these studies is usually quantified by some measure of goodness of fit of the model predictions to the actual fault data, or using within-system cross-validation techniques, such as V-cross-validation [13].

The purpose of building such models is to apply them to other systems (e.g., different systems developed in the same development environment), in order to focus verification and validation efforts on fault-prone parts of those systems. But little is known about the accuracy of prediction models when they are actually applied under realistic conditions. In that sense, the existing studies can mostly be characterized as feasibility studies.

In this paper, we build a fault-proneness prediction model based on a set of OO measures using data collected from a mid-sized Java system, and then apply the model to a different Java system developed by the same team. We then evaluate the accuracy of the model’s prediction in that system and the model’s economic viability using a cost-benefit model.

A second objective is to use a novel exploratory, regression-based technique called MARS (Multivariate Adaptive Regression Splines [11]). We investigate whether this technique can result in more accurate fault-proneness models than typical logistic regression models assuming a linear relationship between covariates and the logit term. Model functional forms are difficult to determine a priori as we do not have credible, precise theories to devise them.

Results indicate that a model built on one system can be used to accurately rank classes within another system according to their fault-proneness. However, only the MARS model is accurate whereas the linear logistic regression model does not seem appropriate. A cost-benefit model demonstrates such a fault-proneness model is potentially viable as it can provide clear benefits. However, the probabilities of a model built on one system applied to another suggest that differences in system factors make these probabilities meaningless, though the class ranking is preserved. In other words, if this is confirmed, such models’ probabilities would need to be calibrated for each system. The implications of such a limitation are discussed below.

The paper is structured as follows. Section 2 describes the setting of the study. Section 3 briefly lays down our analysis methodology and introduces the modeling techniques, logistic regression, and MARS. Analysis results are detailed in Section 4, and we draw our conclusions in Section 5.
2 DESCRIPTION OF STUDY SETTING

This section describes the systems used for this study, the data collected, and the data collection procedures.

2.1 Systems

This subsection provides details about the two Java systems used in this study, Xpose and Jwriter, both developed at Oracle Brazil. Jwriter was developed first and then Xpose started. But Xpose is the larger of the two systems in terms of fault data and number classes, and as such more fit for us to build a prediction model. We will therefore use Xpose for the fit data set from which we build our prediction models. Jwriter, the smaller system, will be used as test data set.

We try to put ourselves in a situation where one would have sufficient\(^1\) design and fault data from one or a few projects and would use such data to build fault-proneness models to be used on new projects. Though, due to the characteristics of the data sets at hand, we had to use the two projects in their reverse order of performance (Xpose and Jwriter are used to build and test the model, respectively), we believe this has no effect on answering our research questions: the differences between projects are still there and are going to affect the model’s accuracy. Our research design will simply have implications in the way we interpret the results.

2.1.1 Xpose

Xpose for Java is an application that allows its users to display and edit XML documents. With Xpose one can traverse an XML document’s hierarchy, explore the attributes of a particular node in that hierarchy, or view and edit the XML source associated with it. The application offers a Document Browser, an XML rendering machine, and a property inspector and contents editor to view and modify XML elements.

Xpose was implemented under Sun’s JDK 1.2, using the Swing library classes for the GUI, and a prefabricated XML Parser also developed at Oracle. Xpose consists of 144 Java classes, with a total of 1774 methods. Some of the 144 classes were reused with modifications.

2.1.2 Jwriter

Jwriter is a component that provides basic word processing capabilities, i.e., text editing, formatting at the word, paragraph and document level, definition of styles (groups of formatting elements), support for file formats (RTF, HTML), in-document images, automated spell checking, and connectivity to Oracle Databases. Jwriter can be used standalone or integrated in other applications that need to provide word processing capabilities.

Jwriter was developed under Sun JDK 1.1, using Swing and a set of prefabricated toolkits for RTF and HTML data exchange, and spell checking support. Jwriter consists of 68 Java classes, with a total of 933 methods.

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\(^1\) This is subjective and context dependent but, as a ballpark figure, our experience suggests that at least 100 observations (classes) are needed to account for the complexity of such fault-proneness models. As discussed below, Jwriter only contains 68 classes.

2.2 Data Collection Procedures and Measurement Instruments

For both Xpose and Jwriter the following relevant items were collected:

- the source code of the systems.
- data about faults found in the field by customers

A static analyzer (Jmetrics, developed by Oracle Brazil) was developed to extract the values for the object-oriented design measures directly from the source code of Xpose and Jwriter.

One issue that has usually to be dealt with when analyzing design measures and fault data is that systems are being measured at a given version and keep evolving. We therefore have to decide what version we measure and what fault data we consider. The way to address this issue is context dependent. When building fault-proneness models with Xpose fault data, we will use all faults that have been detected after version 1.17. We collected our design measurements on that version and the class interfaces, on which are based the design measures we used, have not changed significantly after that version. When we will apply our fault-proneness model to Jwriter, we will apply it to version 0.5 (the first delivered version) and use the fault data for that version. We therefore emulate the situation where we would build a model based on the fault history of a system and then apply it to a new system that has just been developed.

2.3 Dependent Variable

We want to evaluate whether existing OO design measures are useful for predicting the probability that a fault is detected in a class during field use. More precisely, the probability of fault detection that is meant here is a conditional probability: the probability that at least one failure occurring in the field is traced back to a fault in a class, depending on the obtained measurement values of the design measures for that class. This should be a good indicator of the class fault-proneness.

2.4 Independent Variables

The set of design measures investigated in this study includes a subset of the coupling measures described in [3] [5], a set of measures related to polymorphism [1], a subset of the OO measurement suite of Chidamber and Kemerer [8], and some simple size measures based on counts of the methods and attributes. The Appendix contains a summary of the measures we used, as collected by Jmetrics.

Some of the classes in Xpose and Jwriter contain Java inner classes. These inner classes were not treated as individual observations (data points) in this study. Instead, in the calculation of our design measures, methods and attributes of inner classes were counted to contribute towards the containing class. Accordingly, faults traced back to an inner class were assigned to the outmost containing class. Clearly, other strategies to deal with inner classes are possible, e.g., by treating them as individual observations and adjusting the measures accordingly.
This choice entirely depends on how the results prediction models are intended to be used. If we want inner classes to be inspection objects that our prediction model can point to, we need to treat them as separate observations. Then, the fault data has to be collected at this finer level of granularity.

3 DATA ANALYSIS METHODOLOGY

In this section we describe the methodology used to analyze the OO measurement data collected. The analysis procedure comprises an analysis of the descriptive statistics, principal component analysis, univariate regression analysis against the fault data. The reader is referred [4] to for a detailed description and justification of our analysis procedures.

3.1 Descriptive statistics

The distribution and variance of each measure is examined to select those with enough variance for further analysis. Low variance measures do not differentiate classes very well and therefore will not be useful predictors in our data set. Furthermore, a comparison of the descriptive statistics between the two systems will help us better interpret the results of our analysis below.

3.2 Principal component analysis

If a group of variables in a data set are strongly correlated, these variables are likely to measure the same underlying dimension (i.e., class property) of the object to be measured. Principal component analysis (PCA) is a standard technique to identify the underlying, orthogonal dimensions that explain relations between the variables in the data set. Principal components (PCs) are linear combinations of the standardized independent variables. The sum of the square of the coefficients in each linear combination is equal to one. PCs are calculated as follows. The first PC is the linear combination of all standardized variables that explain a maximum amount of variance in the data set. The second and subsequent PCs are linear combinations of all standardized variables, where each new PC is orthogonal to all previously calculated PCs and captures a maximum variance under these conditions. Usually, only a subset of all variables have large coefficients - also called the loading of the variable - and therefore contribute significantly to the variance of each PC. The variables with high loadings help identify the dimension the PC is capturing but this usually requires some degree of interpretation.

In order to identify these variables, and interpret the PCs, we consider the rotated components. This is a technique where the PCs are subjected to an orthogonal rotation. As a result, the rotated components show a clearer pattern of loadings, where the variables either have a very low or high loading, thus showing either a negligible or a significant impact on the PC. There exist several strategies to perform such a rotation. We used the varimax rotation, which is the most frequently used strategy in the literature. See [10] for more details on PCA and rotated components.

3.3 Univariate and multivariate regression analysis

Univariate logistic regression analysis is performed for each individual measure (independent variable) against the dependent variable, i.e., no fault/fault detection, in order to determine if the measure is a useful predictor of fault-proneness.

Next, we build multivariate prediction models using logistic regression. This analysis is conducted to determine how well we can predict the fault-proneness of classes, when the measures are used in combination. The covariates of the models are determined by using a mixed stepwise selection heuristic [12], which aims at identifying a subset of the available measures with a high goodness of fit to the data. We build two types of prediction models:

- Using the OO design measures directly as covariates
- Using the basic functions from MARS as covariates

This combination of Mars and logistic regression is purported to yield higher accuracy models, having a more realistic functional form.

Details about logistic regression and MARS are given in the following sections.

3.3.1 Logistic regression

The dependent variable we use to validate the design measures is binary, i.e., was a failure found in acceptance testing traced back to a fault in a class? Therefore, we use logistic regression, a standard technique based on maximum likelihood estimation, for the regression analysis. In the following, we give a short introduction to logistic regression, full details can be found in [12].

A multivariate logistic regression model is based on the following relationship equation (the univariate model is a special case of this, where only one independent variable appears):

\[
\pi (X_1, \ldots, X_n) = \frac{e^{(c_0 + c_1X_1 + \cdots + c_nX_n)}}{1 + e^{(c_0 + c_1X_1 + \cdots + c_nX_n)}}
\]

\(\pi\) is the probability that a fault was traced back to a class after a failure during operation, and the \(X_i\)s are the design measures included as independent variables in the model (also called covariates).

Our dependent variable, \(\pi\), is a conditional probability: the probability that a fault is found in a class, as a function of the class’ structural properties. The curve between \(\pi\) and a single \(X_i\) – assuming that all other \(X_i\)s are constant – takes a flexible S shape which ranges between two extreme cases:

- When \(X_i\) is not significant, then the curve approximates a horizontal line, i.e., \(\pi\) does not depend on \(X_i\).
- When \(X_i\) entirely differentiates fault-prone software parts from the ones that are not, then the curve approximates a step function.

\(^2\) Other heuristics, such as using principal component analysis to pre-select variables, were tried but did not result in significant differences.
Such an S shape is perfectly suitable as long as the relationship between Xis and π is monotonic, an assumption consistent with our empirical hypotheses regarding the design measures. Otherwise, higher degree terms have to be introduced in the regression equation.

3.3.2 MARS

When analyzing and modeling the relationship between fault detection and inspection effort, as well as other potential effectiveness factors mentioned earlier, one of the main issues is that relationships between these variables are expected to be complex (non-linear) and to involve interaction effects. Because we currently know little about what to expect and because such relationships are also expected to vary from one organization to another, analyzing inspection data in order to understand what affects inspections’ effectiveness is usually a rather complex, exploratory process.

When using typical regression techniques, the risk to fit the data with models that may be simplistic is rather difficult to avoid. For example, we typically resort to log-linear models to handle non-linear relationships. But this comes with a number of drawbacks such as forcing the model to have a null intercept or making the analysis of interactions impossible (the whole log-linear model is a multiplicative expression). An alternative to model such complex relationships is artificial neural networks [7]. However, such models are difficult to interpret [7] as it is nearly impossible to assess the impact of individual independent variables on the dependent variables and their interactions. Interpretation is key in our context, as the models we build are not just used for prediction purposes but are also used to support decision-making and, from a more general perspective, gain a better understanding of software engineering processes.

MARS is a novel statistical method presented in [11] and supported by a recent tool developed by Salford Systems1. At a high level, MARS attempts to approximate complex relationships by a series of linear regressions on different intervals of the independent variable ranges (i.e., subregions of the independent variable space). It is very flexible as it can adapt any functional form and is thus suitable to exploratory data analysis. One challenge though is to find the appropriate intervals on which to run independent linear regressions, for each independent variable, and identify interactions while avoiding overfitting the data. This is the purpose of the search algorithms proposed by the MARS methodology. Though these algorithms are complex and out of the scope of this paper, MARS is based on a number of simple principles. They are introduced below in order for the reader to understand the results presented in later sections. It is also interesting to note that the results in [7] show that for datasets of sizes comparable to what we use in this study, MARS models are more likely to be accurate than artificial neural networks.

1 www.salford-systems.com

Figure 1 illustrates a simple example of how MARS would attempt to fit data, in a two dimension space (where Y and X are the dependent and independent variables, respectively), with piece-wise linear regression splines. A key concept is the notion of knots, that are the points that mark the end of region of data where a distinct linear regression is run, i.e., where the behavior of the modeled function changes. Figure 1 shows two knots: x1 and x2. They delimit three intervals where different linear relationships are identified. MARS search algorithms identify appropriate knots in an automated way, though a number of search parameters have to be set by the user. Of course, in a case with higher dimensions and interactions between independent variables, the search becomes much more complex but the fundamental principles remain the same. The reader is referred to [11] for further details.

In order to model the concept of knots and piece-wise linear regression splines, MARS uses the concept of basis function. These are functions of the form:

\[
\text{max}(0, X-c), \quad \text{or} \quad \text{max}(0, c-X)
\]

where X is an independent variable and c a constant.

Such basis functions re-express an independent variable X by mapping it to new variables, which are basis functions of the form described above. For \text{max}(0, X-c), X is set to 0 for all values of X up to some threshold value c and is equal to X for all values of X greater than c. By mixing the two types of basis functions presented above and providing adequate values for c, it is possible to approximate any functional shape. Determining the right knots (threshold values c) is a key challenge addressed by MARS search algorithms. In short, basis functions are used as the new independent variables of our regression estimation models. MARS also looks for interaction terms among basis functions, thus leading to the modeling of the interactions among independent variables.

In this paper, we are building a classification model. Our dependent variable is binary. From the short introduction above, it is clear that basis functions are identified assum-
ing the dependent variable is continuous. In this context, as recommended in [11], we use MARS in two steps: (1) Use the MARS algorithms to identify relevant basis functions, (2) Refit the model with logistic regression, using the basis functions as covariates.

### 3.4 Model Evaluation

We evaluate the accuracy of our prediction models in terms of correctness and completeness, two standard measures used for classification techniques. The model predicts classes as either fault-prone or not fault-prone.

**Correctness** is the number of classes correctly classified as fault-prone, divided by the total number of classes classified as fault-prone. Low correctness means that a high percentage of the classes being classified as fault-prone do not actually contain a fault. We want correctness to be high, as inspections of classes that do not contain faults is a waste of resources.

**Completeness** is defined as the number of faults in classes classified fault-prone, divided by the total number of faults in the system. It is a measure of the percentage of faults that would have been found if we used the prediction model in the stated manner. Low completeness indicates that many faults would have been found if we used the prediction model in contexts:

- V-cross-validation within Xpose. V-cross-validation [13] is a technique to obtain realistic estimate of the predictive power of prediction models, when they are applied to data sets other than those the models were derived from, but no other test data set is available. In short, a V-cross validation divides the dataset into V parts, each part being used to assess a model built on the remainder of the dataset. In our study, we will divide our 144 observations dataset into 10 randomly selected parts and perform a 10-cross validation.
- Cross-system validation consists of applying the prediction model built from one data set (Xpose) to a different data set (Jwriter), and assess the accuracy of these predictions. We use the larger, and therefore more representative data set of Xpose as fit data, and Jwriter as test data.

### 3.5 Cost-benefit Model

We need to define a cost-benefit model that helps us determine whether a given fault-proneness model would be economically viable. We propose a model below that makes a number of assumptions.

- All classes predicted fault-prone are inspected
- The average inspection effectiveness $e \leq 1$, where $e = 1$ means that all faults in inspected classes are being detected
- For computing a benefit, we need a baseline of comparison and this is what would happen if classes to be inspected were selected by chance

We will use the count definitions in the following classification table where $n_i$’s are class frequencies and $f_i$’s are faults frequencies in the corresponding classes:

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No fault</td>
</tr>
<tr>
<td>(\pi_{\text{SP}}) (not faulty)</td>
<td>$n_{11}$</td>
</tr>
<tr>
<td>(\pi_{\text{SP}}) (faulty)</td>
<td>$n_{21}$</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>$n_{1x}$</td>
</tr>
</tbody>
</table>

The average cost of inspection per class is $ic$ and the average cost of a fault when not detected during inspection is $fc$.

Gains and losses are all expressed below in effort units, i.e., the effort saved and the effort incurred assuming inspections are performed on code, for example.

When using a fault-proneness model, the gain and cost of using the model can be expressed as:

**Gain (effort saved)**: $g$

\[ g = defects\, covered\, and\, found \]

\[ g = f_{22} \cdot e \cdot fc \]

**Cost (effort incurred)**: $c$

\[ c = direct\, inspection\, cost + defects\, not\, covered + defects\, that\, escape \]

\[ c = n_{2x} \cdot ic + f_{12} \cdot fc + (1-e) \cdot f_{22} \cdot fc \]

Similarly, when using no fault-proneness model, just selecting classes by chance, the gain and cost of using the model can be expressed as:

\[ g = (n_{2x} / n) \cdot f \cdot e \cdot fc \]

\[ c = n_{2x} \cdot ic + (n_{1x} / n) \cdot f \cdot fc + (1-e) \cdot (n_{2x} / n) \cdot f \cdot fc \]

Note that another assumption behind this model is that the proportion of defects in randomly selected classes to inspect is the proportion of the number of classes selected.

What we now want to assess is the difference in cost and gain when using and not using a fault-proneness model.

\[ \Delta\text{gain} = f_{22} - (n_{2x} / n) \cdot f \cdot e \cdot fc \]

\[ \Delta\text{cost} = fc ((f_{22} - (n_{2x} / n) \cdot f) + (1-e) \cdot (f_{22} - (n_{2x} / n) \cdot f)) \]

The benefit of using the prediction model to select classes for inspection instead of selecting them randomly is

\[ \text{benefit} = \Delta\text{gain} - \Delta\text{cost} \]

In the formula for $\Delta\text{cost}$, by substituting $n_{1x} = n-n_{2x}$ and $f_{12} = f_{f-22}$, we obtain

\[ \Delta\text{cost} = fc ((f-f_{22} - (n_{2x} / n) -1) \cdot f) \]

\[ + (1-e) \cdot (f_{22} - (n_{2x} / n) \cdot f)) \]

and, by doing the multiplications and adding summands,

\[ \Delta\text{cost} = fc (-e \cdot f_{22} + e \cdot (n_{2x} / n) \cdot f) = - \Delta\text{gain} \]

hence

\[ \text{benefit} = \Delta\text{gain} - \Delta\text{cost} = 2 \cdot \Delta\text{gain} \]
As we will see below, this will allow us, for a given range of \( e \) values, to determine the benefits of using a fault-proneness model in function of \( fc \), the cost of a defect slipping through inspections. Both \( e \) and \( fc \) are context-dependent but it will still allow us to assess the order of magnitude of the model net benefits, if any.

4 ANALYSIS RESULTS

In this section we present the details on our analysis results. We start off with the descriptive statistics of the design measures collected for Jwriter and Xpose (Section 4.1). We then perform principal component analysis (Section 4.2), univariate analysis (Section 4.3) and multivariate analysis using logistic regression and MARS to build and evaluate prediction models from Xpose data set (Section 4.4). In Section 4.5, we apply the prediction model to Jwriter.

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the Xpose and Jwriter. Columns “Max”, “75%”, “Med.”, “25%”, “Min.”, “Mean” and “Std Dev” state for each measure the maximum value, 75% quartile, median, 25% quartile, minimum, mean value, and standard deviation, respectively.

For Xpose, the use of inheritance is sparse (low mean values of DIT, NOC, note that in this study the DIT of a root class is 1). This has already been found in many systems before [4][5][8][9]. As a consequence, the polymorphism measures from [1], and the measures counting coupling from/to ancestors/descendents too show low means and standard deviations. The measure DCAEC, DCMEC, SPD, and DPD have nonzero values only for very few (six or less) classes, we therefore drop these measures from the remainder of the analysis.

Turning the discussion to Jwriter, inheritance is even less frequently used there (average DIT is 1.2). Measures DCAEC, DCMEC, and SPD do not vary at all in this system. While the number of methods (totmethod, totprivmethod) shows remarkably similar distributions in both systems, the number of attributes (totattrib, totprivattrib) in Jwriter is about a factor three higher than in Xpose (and therefore, aggregation coupling is higher, too).

To conclude, even though the systems stem from the same development environment, the distributions of the measures vary considerably in some cases. This is certainly not an ideal situation for our goal to apply prediction models across systems but it may be a realistic one. The differences in distributions may be partly due to the fact that Xpose had a more experienced project manager in OO analysis and design, though the development team was the same. In addition, the team was more experienced when Xpose started, and they used design by contract and enforced much more rigorous programming standards. All this may have helped them identify better objects and classes, and devise a better system class diagram. From a more general standpoint, in any organization, practices are likely to evolve over time, as people gain more experience and as key personnel changes. So our datasets may reflect realistic conditions under which fault-proneness models have to be used. We will discuss further the implications in our analysis below.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Xpose, based on 144 classes</th>
<th>Jwriter, based on 68 classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPA</td>
<td>0.215 0.711 5 0 0 0 0 0.265 1.074 8 0 0 0 0</td>
<td>SPA</td>
</tr>
<tr>
<td>DPA</td>
<td>1.09 2.975 16 0 0 0 0 1.691 4.016 20 1.5 0 0 0</td>
<td>DPA</td>
</tr>
<tr>
<td>SPD</td>
<td>0.076 0.474 5 0 0 0 0 0 0 0 0 0 0 0</td>
<td>SPD</td>
</tr>
<tr>
<td>DPD</td>
<td>0.778 6.692 78 0 0 0 0 0.75 3.735 28 0 0 0 0</td>
<td>DPD</td>
</tr>
<tr>
<td>SP</td>
<td>0.292 0.838 5 0 0 0 0 0 0 0 0 0 0 0</td>
<td>SP</td>
</tr>
<tr>
<td>DP</td>
<td>1.868 7.291 78 1 0 0 0 2.441 5.863 30 2.5 0 0 0</td>
<td>DP</td>
</tr>
<tr>
<td>NIP</td>
<td>30.94 37.435 199 44 17 4 0 46.16 40.2 145 63 41.5 11 0</td>
<td>NIP</td>
</tr>
<tr>
<td>DIT</td>
<td>2.41 5.354 42 2 0 0 0 1.911 2.728 19 2 0 0 0</td>
<td>DIT</td>
</tr>
<tr>
<td>NOC</td>
<td>0.556 3.083 29 0 0 0 0 0.191 0.629 3 0 0 0 0</td>
<td>NOC</td>
</tr>
<tr>
<td>Totattrib</td>
<td>2.056 5.081 57 2 0 0 0 2.353 4.367 19 2.5 1 0 0</td>
<td>Totattrib</td>
</tr>
<tr>
<td>Totprivattrib</td>
<td>2.944 4.696 24 4 0 0 0 6.397 9.709 39 9 1 0 0</td>
<td>Totprivattrib</td>
</tr>
<tr>
<td>Totprivmethod</td>
<td>3.285 4.697 24 5 1 0 0 9.279 10.78 41 14 7 0.5 0</td>
<td>Totprivmethod</td>
</tr>
<tr>
<td>Totmethod</td>
<td>12.32 13.864 83 18 7 3 0 13.72 12.12 66 19 9 6 1</td>
<td>Totmethod</td>
</tr>
</tbody>
</table>

Table 1 Descriptive Statistics for Xpose and Jwriter
4.2 Principal Component Analysis

Table 2 shows the results from PCA performed on the Xpose data set. We identified six orthogonal dimensions capturing 76% of the data set variance. For each PC, we provide its eigenvalue, the variance of the data set explained by the PC (in percent), and the cumulative variance. Below are the loadings of each measure in each rotated component. Values above 0.7 are set in boldface, these are the measures we call into play when we interpret the PCs.

<table>
<thead>
<tr>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>PC6</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>PC2</td>
<td>PC3</td>
<td>PC4</td>
<td>PC5</td>
<td>PC6</td>
</tr>
<tr>
<td>EigenValue:</td>
<td>5.977</td>
<td>2.189</td>
<td>1.515</td>
<td>1.439</td>
<td>1.372</td>
</tr>
<tr>
<td>CumPercent:</td>
<td>33.205</td>
<td>45.366</td>
<td>53.781</td>
<td>61.776</td>
<td>69.397</td>
</tr>
<tr>
<td>TotMethod</td>
<td>-0.347</td>
<td>0.053</td>
<td>0.019</td>
<td>-0.082</td>
<td>0.272</td>
</tr>
<tr>
<td>TotPrivMeth.</td>
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<td>0.019</td>
<td>0.080</td>
<td>0.080</td>
<td>0.010</td>
</tr>
<tr>
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<td>0.223</td>
<td>-0.153</td>
<td>0.070</td>
<td>0.070</td>
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<tr>
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<td>0.019</td>
<td>0.080</td>
<td></td>
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</tr>
<tr>
<td>NOC</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DIT</td>
<td>0.053</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OCMEC</td>
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<td>0.019</td>
<td>0.080</td>
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<td></td>
</tr>
<tr>
<td>OCMIC</td>
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<td>0.019</td>
<td>0.080</td>
<td></td>
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</tr>
<tr>
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<td>0.080</td>
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<tr>
<td>OCAIC</td>
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<td></td>
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<tr>
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<td>0.080</td>
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<td></td>
</tr>
<tr>
<td>DP</td>
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<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DPA</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPA</td>
<td>0.070</td>
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<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OVO</td>
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<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIP</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DPA</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPA</td>
<td>0.070</td>
<td>0.019</td>
<td>0.080</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2 Rotated Components for Xpose data set

Based on the loadings of the measures in each rotated component, the PCs are interpreted as follows:
- **PC1**: Class size, in terms of attributes and methods
- **PC2**: The number of children / descendents of a class
- **PC3**: Amount of polymorphism taking place
- **PC4**: Export coupling to other classes
- **PC5**: Import coupling to ancestor classes
- **PC6**: OVO

These results in part do confirm earlier findings, that import and export coupling to ancestors/ascendants/other classes tend to span orthogonal dimensions, and that import coupling measures are somewhat associated with size measures. Note that the loadings in PC1 are not as strong as in the other PCs, the correlation between OCAIC and TotAtrib as measured by Pearson’s r is 0.7, i.e., the measures explain less than 50 percent of the variation of each other.

4.3 Univariate Analysis

The results of the univariate analysis on Xpose are summarized in Table 3. For each measure, the regression coefficient, along with its standard error, and the statistical significance (p-value), which is the probability that the coefficient is different from zero by are provided (see columns “Msr.”, “S.E.”, “p-val “, respectively).

<table>
<thead>
<tr>
<th>Msr.</th>
<th>Coef.</th>
<th>S.E.</th>
<th>p-val</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPA</td>
<td>0.719</td>
<td>0.306</td>
<td>0.019</td>
</tr>
<tr>
<td>DPA</td>
<td>0.241</td>
<td>0.075</td>
<td>0.001</td>
</tr>
<tr>
<td>SP</td>
<td>0.624</td>
<td>0.246</td>
<td>0.011</td>
</tr>
<tr>
<td>DP</td>
<td>0.242</td>
<td>0.069</td>
<td>0.000</td>
</tr>
<tr>
<td>NIP</td>
<td>0.042</td>
<td>0.008</td>
<td>0.000</td>
</tr>
<tr>
<td>OVO</td>
<td>0.026</td>
<td>0.033</td>
<td>0.428</td>
</tr>
<tr>
<td>ACAIC</td>
<td>0.625</td>
<td>0.334</td>
<td>0.062</td>
</tr>
<tr>
<td>ACMIC</td>
<td>0.171</td>
<td>0.066</td>
<td>0.010</td>
</tr>
<tr>
<td>OCAIC</td>
<td>0.536</td>
<td>0.142</td>
<td>0.000</td>
</tr>
<tr>
<td>OCAEC</td>
<td>0.147</td>
<td>0.099</td>
<td>0.137</td>
</tr>
<tr>
<td>OCMIC</td>
<td>0.447</td>
<td>0.092</td>
<td>0.000</td>
</tr>
<tr>
<td>OCMEC</td>
<td>0.099</td>
<td>0.041</td>
<td>0.016</td>
</tr>
<tr>
<td>DIT</td>
<td>0.182</td>
<td>0.106</td>
<td>0.086</td>
</tr>
<tr>
<td>NOC</td>
<td>0.740</td>
<td>0.380</td>
<td>0.052</td>
</tr>
<tr>
<td>TotAtrib</td>
<td>0.224</td>
<td>0.054</td>
<td>0.000</td>
</tr>
<tr>
<td>TotPrivAtrib</td>
<td>0.233</td>
<td>0.053</td>
<td>0.000</td>
</tr>
<tr>
<td>TotPrivMeth.</td>
<td>0.183</td>
<td>0.057</td>
<td>0.001</td>
</tr>
<tr>
<td>TotMethod</td>
<td>0.087</td>
<td>0.020</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 3 Univariate Analysis Results for Xpose

As is visible from Table 3, most measures are found to be significantly (α=0.05) related with fault-proneness. All regression coefficients are positive, i.e., the higher coupling, polymorphism, or size of the class, the higher its fault-proneness. This is consistent with the general hypotheses associated with these measures [5][1], and confirms results from earlier studies [4][5].

Inheritance measures show a weak trend with fault-proneness (deeper classes and classes with a higher number of children are fault-prone). However, these trends are not significant at α=0.05. Also, this result is yet again different from what was found in [4], where deeper classes too were more fault-prone, but classes with higher NOC were less fault-prone, and [5], where deeper classes were less fault-prone, and NOC not significant at all. As discussed in [5], the impact of inheritance is likely to vary according to the inheritance strategy used and the experience of designers.

4.4 Multivariate Analysis

In this section we present the multivariate prediction models that were built for the Xpose data set, using a mixed stepwise selection procedure [12]. Two models were built, a “linear” model (Section 4.4.1) that uses directly the design measures as independent variables, and a MARS model (Section 4.4.2) that uses the MARS basic functions as covariates.

We also assess the model accuracy using a 10-cross-validation within Xpose. This is done for two purposes:

---

4 However, this may be due in part to repeated testing that increases the probability to find a significant relationship by chance. Though they are simple techniques to address this problem, e.g., Bonferroni procedure: divide your significance level (α) by the number tests performed, we use only univariate analysis here as a first variable pre-selection stage. As a result, we will not use here any technique to alleviate the problems due to repeated statistical testing.
• To compare the model accuracy to results from previous studies, which also performed 10-cross-validation within the same system.
• To establish a comparison baseline when the models are then applied to the Jwriter data set in Section 4.5.

4.4.1 Linear Model
The multivariate linear model is shown in Table 4. The stepwise variable selection procedure retained an import coupling measure (OCMIC), an export coupling measure (OCMEC), and NIP (belonging to the “class size” dimension as described in Section 4.2) in the model. This is consistent with previous results \cite{4,5} where class size, import coupling and, to a lesser extent, export coupling play a role in fault-proneness.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Coeff</th>
<th>Std. Err</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIP</td>
<td>0.031</td>
<td>0.009</td>
<td>0.001</td>
</tr>
<tr>
<td>OCMIC</td>
<td>0.216</td>
<td>0.097</td>
<td>0.026</td>
</tr>
<tr>
<td>OCMEC</td>
<td>0.066</td>
<td>0.034</td>
<td>0.055</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.355</td>
<td>0.492</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 4 Linear Model

The results from performing a 10-cross validation are summarized in Table 5 and Figure 2.

In Table 5, Classes with a predicted probability larger than 0.5 are classified as fault-prone, the others are predicted not fault-prone. The following contingency table shows how predicted and actual faulty classes overlap, and how many faults are contained by faulty classes, whether predicted faulty or not. 14 out of the 19 classes that are predicted fault-prone actually do contain a fault (73.6% correctness), these classes contain 82 out of the 132 faults in the system (62% completeness).

While the model is capable of identifying 19 out of 144 classes (i.e., 13% of all classes), which contain over 60% of all faults, the fact that we still miss 40% of the faults if we relied on the model prediction may hamper the model’s practicality. We will investigate below this issue using the cost-benefit model introduced in Section 3.4.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Coeff</th>
<th>Std. Err</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OCMIC</td>
<td>0.9474947</td>
<td>0.1881999</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>BF5</td>
<td>-0.24392427</td>
<td>0.0644459</td>
<td>0.0002</td>
</tr>
<tr>
<td>BF6</td>
<td>0.0962286</td>
<td>0.0553</td>
<td>0.0818</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.87</td>
<td>0.40756</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Table 6 Mars Model

The MARS model is similar to the linear model in the sense that it involves OCMIC and OCMEC, the latter being a weaker predictor. The difference is that DIT is selected as opposed to NIP in the linear model. Also, DIT clearly interacts with OCMIC. The sign of the coefficient of BF5 suggests that OCMIC has a stronger impact when DIT increases, that is import coupling impacts fault-proneness further at deeper levels of inheritance. Though more investigation is required, the compound effect of inherited and imported class elements may generate an even higher complexity in terms of understanding and verifying classes.

Below is the contingency table that results when we apply the 10-cross validation to the MARS model. 15 of the 22 classes predicted fault-prone actually are faulty (68% correctness), these classes contain 97 of the 132 classes (73% completeness).
The MARS model does not show a strong difference with the linear model in terms of correctness. But in terms of completeness, it performs much better than the linear model. In other words, it is more accurate for the classes containing larger numbers of faults. Correctness and completeness as a function of $\pi$ are shown in Figure 3. As can be seen, the chosen cutoff value of 0.5 is in fact a good tradeoff between correctness and completeness for this model.

The benefit is shown as a function of $n_{2x}$, the number of classes selected for inspection, which is itself dependent on the threshold $\pi$. The benefit is expressed in multiples of $fc$, the cost of a fault that goes undetected in inspections, and assumes an inspection effectiveness $e$ of 0.8 (cf. Section 3.5 for how $e$ and $fc$ affect the model benefit). In a literature survey of industry data [2], $fc$ typically ranged between 4.5 and 17 person hours, with a most likely value of 6 person hours. So we can see that the type of benefits illustrated in Figure 4 can represent substantial savings.

Varying the inspection effectiveness $e$ amounts to multiplying the benefit curve by a constant factor. For instance, if we assume an inspection effectiveness only half as high ($e=0.4$), the peak of the curve will be at $66fc$.

4.5 Application of Xpose models to Jwriter

The straightforward way to apply the models built from Xpose to the Jwriter classes is to calculate the predicted fault-proneness for each class in Jwriter; if it is above a certain threshold (e.g., 0.5) the class is considered fault-prone and undergoes inspection, otherwise not.

However, when looking at the probabilities predicted by the Xpose model for Jwriter classes, all of them are between 0 and 0.06. In other words, predicted probabilities are very low. This may be expected considering the differences in distributions across the two systems in terms of inheritance and import/export coupling, the predictor variables of our model. This suggests that at most a few faults should have been found in Jwriter if the development conditions of Jwriter had been similar to the ones of Xpose. But nearly 40% of the classes in Jwriter contained a fault related to a failure in the field. To understand what happened we have to recall the history of these systems. Jwriter was developed first. The team was less experienced with Java, the Java libraries were less mature and contained more bugs, and the
project manager was different. Even the design strategy (design by contract) and the coding standards were much stricter on Xpose. Therefore, relative to its structural properties and for the reasons explained above, Jwriter is much more fault-prone, as a system, than Xpose. From a more general standpoint, this suggests that, in the common situation where development practices are changing and teams are evolving and learning, an absolute interpretation of predicted probabilities will not be possible when they come from prediction models built on different systems. There are system factors that are likely to come into play, even in high maturity development environments. Unfortunately, this hinders us from using probabilities to classify classes according to their fault-proneness and other means of using the fault-proneness models have to be devised.

In order to still be able to use the prediction model from Xpose, we apply a different strategy. Let us try to use the ranking based on fault-proneness probabilities, though the probabilities themselves may not be realistic. We rank the classes of Jwriter by their predicted fault-proneness. Then, we can assume that the N most fault-prone classes will undergo specific and thorough inspection. Now a practical question is: How to select N? When they are representative of a given system, probabilities have meaning and they can be used to make decisions. But rankings are more difficult to use in practice. Selecting N can be done based on historical data telling us, for example, what is the typical proportion of faulty classes.

We will perform one ranking of the entire Jwriter class set according to their predicted fault-proneness. Based on this ranking, we select the N classes with highest predicted fault-proneness. The question then is: how does the maximum number of faults that can be thus detected increase with N? If the prediction model is useful, we would expect the number of faults found to increase sharply in the beginning, and then reach a plateau. Figure 5 shows the cumulative number of faults versus class fault-proneness ranking, based on the predictions of the linear model for the Jwriter data.

The lower straight line is the percentage of faults that we could expect when we randomly rank the classes (number of faults is assumed to be proportional to the number of classes). The upper straight line is what the ideal model would yield, if we were able to rank the 27 faulty classes, containing one fault each, as the 27 most fault-prone classes. We can see in Figure 5 a large hump among the least fault prone classes. This is caused by 7 classes that are unexpectedly faulty, according to the linear model. In short, the curve does not have the shape we would expect and this model does not work very well.

Figure 6 shows the graph that results when we rank the classes by predicted fault-proneness of the MARS model. This figure fits better our expectations than the linear model in the sense that the curve reaches a plateau after rank 35. There is a very small hump towards the end caused by 2 classes having one fault each, but no major abnormality. We can also see that the first 15 most fault-prone classes are almost exclusively faulty and close to the optimal line.

Figure 7 shows the correctness/completeness graph for the MARS model. The best tradeoff between correctness and completeness can be achieved at a cutoff value of 0.04, at which point we have completeness and correctness values of about 50%. These values are lower than what was found for the model in 10-cross-validation. In general, this result suggests that we have to expect a deterioration of the fault-proneness models’ accuracy when they are applied to new systems. And, as stated earlier, predicted probabilities can-
not be subjected to usual interpretations. However, as investigated below, the models can still present benefits.

![Correctness/Completeness for MARS model applied to Jwriter](image1.png)

**Figure 7: Correctness/completeness for MARS model applied to Jwriter**

**Figure 8** shows the benefit curves for the linear and MARS model, respectively, again assuming inspection effectiveness of $e=0.8$. The MARS model reaches its peak rather late (at $n_x=36$ classes select for inspection, i.e., more than half of the Jwriter classes), and the maximum benefit of 12fc is lower than for Xpose, too (note, however, that Jwriter is smaller, an absolute comparison with the 10-cross validation results in Xpose is not possible). The linear model even shows a negative benefit at around $n_x=15$, indicating that the model is not better than chance there. On the other hand, the MARS model clearly shows benefits for practically interesting values of $n_x$ but, as would be expected, not on the extreme right of the graph when more than 60 classes are selected for inspections. The MARS model benefit curves clearly shows that clear benefits can be obtained in using such a model to select classes to undertake (additional) inspections or testing.

We further investigate the performance of the MARS model. We want to determine whether the detection of faults would increase faster than the number of methods inspected (size). This is important, from a practical standpoint, as we would like to detect more faults having to inspect less code. We therefore normalize the number of methods and faults by their respective total to express them as a percentage. The result is shown in **Figure 9**, which contains the cumulative number of faults (upper curve) vs. cumulative number of methods (lower curve).

In Figure 9, we reach a maximum of 20% difference between the percentages of methods and faults, before starting a plateau. This demonstrates that the ranking is able to identify classes with higher fault-density. Also, the lower curve approximates a linear growth, which indicates that the ranking performed by our model is significantly different from the ranking of the classes by their number of methods.

![Benefit Curve of Linear and MARS models for Jwriter (inspection effectiveness e=80%)](image2.png)

**Figure 8: Benefit Curve of Linear and MARS models for Jwriter (inspection effectiveness e=80%)**

![Cumulative faults versus number of methods in percent](image3.png)

**Figure 9 Cumulative faults versus number of methods in percent**

![Cumulative faults versus size ranking (based on number of methods in the class)](image4.png)

**Figure 10 Cumulative faults versus size ranking (based on number of methods in the class)**

Furthermore, when we rank the classes by the number of methods in decreasing order, and look at the cumulative...
number of faults, we obtain Figure 10. The curve appears close to the chance line for the 20 predicted most fault-prone classes. In other word, with this ranking we only catch as many faults as could be expected by the number of selected classes alone. Thus, the class ranking produced by the MARS model built from the Xpose data set is not outperformed by a simple strategy that would be immediately applicable within Jwriter. This further justifies the use of a model such as the one we developed using the Xpose data. Note that when using the number of data members or attributes as a size measure, results are very similar to what we observe or number of methods.

The benefit curve for the size model is shown in Figure 11. Its performance lies between the MARS model and the linear model. Again, the benefit of using the MARS model instead of a simple size model is clear when comparing Figure 11 to the MARS curve in Figure 8. In addition, using a size-based model would lead to a fast increase in inspected material (e.g., code, design) as larger classes would by definition be selected first. As future work, we plan to enhance our benefit model by including class size as a cost parameter.

![Figure 11: Benefit curve for the size-based ranking model (based on number of methods)](image)

4.6 Using Fault-proneness Models to Quantify Quality Improvement

We have seen above that Jwriter was far more fault-prone than what would be expected based on the number of selected classes alone. Thus, the class ranking produced by the MARS model built from the Xpose data set is not outperformed by a simple strategy that would be immediately applicable within Jwriter. This further justifies the use of a model such as the one we developed using the Xpose data. Note that when using the number of data members or attributes as a size measure, results are very similar to what we observe or number of methods.

The benefit curve for the size model is shown in Figure 11. Its performance lies between the MARS model and the linear model. Again, the benefit of using the MARS model instead of a simple size model is clear when comparing Figure 11 to the MARS curve in Figure 8. In addition, using a size-based model would lead to a fast increase in inspected material (e.g., code, design) as larger classes would by definition be selected first. As future work, we plan to enhance our benefit model by including class size as a cost parameter.

4.7 Class Ranking and Iterative Development

Though ranking classes allows us to use the predictions of the Xpose model in Jwriter, there are practical implications if this strategy is to be applied on projects. In order to perform such a ranking, we must first have all classes available for measurement. Object-oriented development, however, is typically iterative. To rank the classes by fault-proneness, we would have to hold inspections until the last iteration, when all classes are fully implemented and ready to be measured. In an iterative development, we could rank the classes within each new iteration and select a certain percentage of the classes with highest ranks in that iteration for inspection. However, we may have iterations with relatively many high-risk classes, then we would select too few classes for inspection. For iterations with few high-risk components, too many classes would be selected for inspection. So we would expect a higher misclassification rate this way, than when we select classes for inspections based on one ranking of the entire data set. This effect should be stronger, the smaller the iterations are.

5 CONCLUSIONS

One of the main objectives of this paper is to assess whether fault-proneness models, based on design measurement, are applicable and can be viable decision making tools when applied from one object-oriented system to the other, in a given environment. This question is of high practical interest as it determines whether such models are worth investigating. But little is currently known about the subject. In this paper we apply a fault-proneness model built on one system to another system. These two systems have been developed with a nearly identical development team (a different project manager), using a similar technology (OO Analysis and design and Java) but different design strategies and coding standards. We believe that the context of our study represents realistic conditions that are often encountered: change in personnel, learning effects, evolution of technology. In this context, we want to assess whether an organization can build viable models to focus verification and validation on fault-prone parts of systems.

Our results suggest that applying the models across systems is far from straightforward. Even though the systems stem from the same development environment, the distributions of measures change and, more importantly, system factors (e.g., experience, design method) affect the applicability of fault detection predicted probabilities. It can be argued that, in a more homogeneous environment, this effect might not be as strongly present as in the current study. But we doubt whether such environments exist or are in any case representative. It is likely, however, that the more stable the development practices and the better trained the developers, the more stable the fault-proneness models.

We then use the prediction model to rank classes of the second system according to their predicted fault-proneness (using the model built on the first system). When used in this manner, the model can in fact be helpful at focusing verification effort on faulty classes. Though predicted defect detection probabilities are clearly not realistic based on actual fault data, the fault-proneness class ranking is accu-
rate. The model performs clearly better than chance and also outperforms a simple model based on class size, e.g., number of methods.

Another objective of the paper is to apply a novel exploratory analysis technique (Multivariate Adaptive Regression Splines: MARS) to the construction of fault-proneness models. Because we know little about what functional form to expect, such exploratory techniques that help finding optimal model specifications may be very useful. Our results support that and suggest that the model generated by MARS outperforms a logistic regression model where the relationship between the logit and the independent variables is linear (log-linear model).

A third contribution of the paper is that we propose and apply a specific cost-benefit model for fault-proneness models. The goal is to assess the economic viability of such fault-proneness models as a function of a number of factors, e.g., defect detection effectiveness. Results suggest that, under realistic assumptions, fault-proneness models can provide substantial benefits, even when used across systems.

Future research needs to focus on collecting larger datasets, involving large numbers of systems from a same environment. It is crucial, in order to make the research on fault-prone models of practical relevance, that they be usable from project to project. Their applicability depends on their capability to predict accurately and precisely (fine grain predictions) where faults lie in new systems, based on the development experience accumulated on past systems.

ACKNOWLEDGMENTS
We would like to thank Dan Steinberg, from Salford Systems, for his advice on the use of the MARS tool (www.salford-systems.com). Also, we wish to thank the software engineers of the Advanced Technology Solution Group from Oracle Brazil: Gonsalo Nunes, Caricio Afonso, Umberto, Paulo Neto, Rafael Farnase, Andre Veiga, and Aristeu Pires for building Xpose, Jwriter, and Jmetrics. Their crucial help was very much appreciated. Amirul Khan should also be thanked for his support in generating some of the graphs. Lionel Briand was supported in part by the Canadian National Science and Engineering Research Council (NSERC).

REFERENCES
All referenced ISERN reports are available at http://www.iese.fhg.de/ISERN.


APPENDIX: DEFINITION OF DESIGN MEASURES

In the following table we provide short definitions of all measures used in the paper. For detailed definitions, references to the source of each measure are provided.

<table>
<thead>
<tr>
<th>Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>spa</td>
<td>Static polymorphism in ancestors</td>
</tr>
<tr>
<td>dpa</td>
<td>Dynamic polymorphism in ancestors</td>
</tr>
<tr>
<td>spd</td>
<td>Static polymorphism in descendants</td>
</tr>
<tr>
<td>dpd</td>
<td>Dynamic polymorphism in descendants</td>
</tr>
<tr>
<td>sp</td>
<td>Static polymorphism in inheritance relations. sp=spa+spd</td>
</tr>
<tr>
<td>dp</td>
<td>Dynamic polymorphism in inheritance relations. dp=spa+spd</td>
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<tr>
<td>nip</td>
<td>Polymorphism in non-inheritance relations</td>
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<tr>
<td>acmic</td>
<td>These coupling measures are counts of interactions between classes (inheritance or not), different types of interactions, and the locus of impact of the interaction.</td>
</tr>
<tr>
<td>dcaec</td>
<td>The acronyms for the measures indicates what interactions are counted:</td>
</tr>
<tr>
<td>dcmec</td>
<td>• The first letter indicates the relationship (A: coupling to ancestor classes, D: Descendents, O: Others, i.e., no inheritance relationships).</td>
</tr>
<tr>
<td>ocaec</td>
<td>• The next two letters indicate the type of interaction:</td>
</tr>
<tr>
<td>ocmic</td>
<td>• CA: Class-Attribute interactions between classes c and d: c has an attribute of type d.</td>
</tr>
<tr>
<td>ocmec</td>
<td>• CM: Class-Method interactions between classes c and d: c has a method with a parameter of type class d.</td>
</tr>
<tr>
<td>dit</td>
<td>The depth of the class in the inheritance tree. Root classes have a DIT of 1 in this paper.</td>
</tr>
<tr>
<td>noc</td>
<td>The number of children of a class.</td>
</tr>
<tr>
<td>totatrib</td>
<td>The total number of attributes in the class</td>
</tr>
<tr>
<td>totprivattrib</td>
<td>The number of private attributes in the class</td>
</tr>
<tr>
<td>totprivmethod</td>
<td>The number of private methods in the class</td>
</tr>
<tr>
<td>totmethod</td>
<td>The total number of methods in the class</td>
</tr>
</tbody>
</table>

Table 8: Definitions of measures