Investigating Defect Prediction Models for Iterative Software Development When Phase Data is Not Recorded
Lessons Learned

Anıl Aydın and Ayça Tarhan
Computer Engineering, Hacettepe University, Ankara, Turkey

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Abstract: One of the biggest problems that software organizations encounter is specifying the resources required and the duration of projects. Organizations that record the number of defects and the effort spent on fixing these defects are able to correctly predict the latent defects in the product and the effort required to remove these latent defects. The use of reliability models reported in the literature is typical to achieve this prediction, but the number of studies that report defect prediction models for iterative software development is scarce. In this article we present a case study which predicts the defectiveness of new releases in an iterative, civil project where defect arrival phase data is not recorded. We investigated Linear Regression Model and Rayleigh Model one of the statistical reliability model that contain time information, to predict the module level and project level defectiveness of the new releases of an iterative project through the iterations. The models were created by using 29 successive releases for the project level and 15 successive releases for the module level defect density data. This article explains the procedures that were applied to generate the defectiveness models and the lessons learned from the studies.

1 INTRODUCTION

As the need for software products increases day by day, the number of software projects that address different types of domains also increase. A few of these projects are developed successfully however; the majority fails (Standish, 2009). The general reason behind this failure is the lack of the ability to specify and plan resources effectively (Jones, 2004; Jones, 2006). If the managers of software projects do not fully envisage the future of their projects, they can neither plan the required resources nor identify the need for project improvement. Thus, the completion of the project will be delayed. This will have a negative impact on customers and the belief in the reliability of the project will be decreased. To overcome these problems, organizations need to allocate resources to estimate and predict some quality measures.

Due to the nature of software development, every software product has defects and the employees spend most of their time on fixing the defective code segments. Estimating and predicting the defectiveness of a software project will give organization an insight into the future of the project; allow the redirection of staff effort to product development and reduce delays in the completion of project to a minimum.

In the literature, there are many studies that propose models which analyze the defectiveness of software products and undertake defect predictions for the future releases. The defect prediction models selected or proposed by these studies generally find solutions to the specific project context (Wahyudin et al., 2011). Finding a general model that fits every software product is hardly realistic. Every project has specific cases, such as the domain of the software project, the software development methodology that is used and the experience of the staff working on the project. These specific cases affect the defect distribution pattern of projects thus, it was necessary to choose an appropriate defect prediction model that best suits our project context (Koru and Liu, 2005).

There are a number of software development methodologies such as; Waterfall, Agile, and Iterative. Each methodology proposes some development methods or techniques. For example, the Waterfall software development methodology contains these phases; Requirements, Design, Development, Test and Deployment which are visited in order and

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only once. Thus, it assumes that before passing to the next phase, all needs of the current phase have to be fulfilled. For this reason, it does not give the flexibility to return to solve problems that had occurred in the previous phases. Therefore, previous phase defects are assumed not to be contained in the latent defects.

Iterative software development, on the other hand, consists of some iterations in the development process to deliver the successive releases of the software product in shorter times (Larman and Basili, 2003). In each iteration, new requirements are identified and for these requirements, each software development phase will be revisited from the beginning. Thus, we can consider each iteration as a mini waterfall (Powell and Spanguolo, 2003). The requirements for an iteration can be summarized as; adding a new feature to the system, updating, changing or removing previously developed features. Unlike Waterfall, the Iterative development methodology gives the flexibility to return and resolve the problems that occurred at previous iterations.

The main goal of this study is to investigate which prediction models best fit the distributions of defect densities at module and project level through the releases of an iterative, civil project in which defect arrival phase data is not recorded. Our study details the experience and the lessons learned from this investigation. As a result of the observations on defect patterns of iterative projects, we decided to use a Linear Regression Model and Rayleigh Software Reliability Model for the module level and project level defect densities through the iterations. For the project level, 70% of all releases′ defect densities were used for the training and constructing of the model and then, 30% of all releases′ defect densities to check the accuracy of the prediction model. For the module level, three separate modules were used for the training and constructing of prediction models and then, the defect density of another module is predicted and the accuracy of the results of the prediction is checked. To check the accuracy and performance of each prediction model, the root mean square error (RMSE), mean absolute error (MAE) and mean magnitude relative error (MMRE) measures were used.

The framework of our study is based on a guideline given by (Runeson and Höst, 2009), and the paper is organized as follows: section 2 presents the Rayleigh and Linear Regression Models; section 3 outlines related studies from the literature; section 4 gives the context of the project to be investigated and the process defect density measure selection. After the measure selection process, the observations on defect density distributions and selections of suitable models that fit best to these distributions are presented and, the analysis procedures of proposed prediction models are given. Then, the model construction and prediction processes are applied and the performances of prediction models are evaluated. At the end of this section, the threats to internal and external validity of this study are presented; section 5 shares the lessons learned during the investigation and section 6 provides an overall conclusion.

2 BACKGROUND

Defect prediction is a process that forecasts the latent defects of a project using specific techniques and models that use historical defect distribution patterns over a time period of the same project or another. In addition to defect prediction, these same models and techniques can be used to predict the defect density and the effort required to remove the defects using historical data. Defects in a software product follow a specific pattern throughout the product′s life time thus, this information helps in the prediction of the latent defects. This process also helps managers to envisage the future of project and estimate and plan the resources effectively. The literature contains several models that can predict latent defects of projects. In this study, the Rayleigh Reliability Model and the Simple Linear Regression Model were used to predict an iterative civil project′s latent defect densities. A description of the models and their functions is given below.

2.1 Rayleigh Model

This reliability model is based on statistical distributions. It is a member of Weibull distribution family and these types of models are generally used to analyze the reliability of engineering products (Kan, 2002). The Rayleigh Model is usually employed to model the distributions of the whole development life cycle of a product. If the defect distribution pattern follows a Rayleigh curve, we can predict the latent defects with using the Rayleigh Model which uses the following two functions to estimate distributions of defects:

a) Probability Distribution Function : This gives an estimation of the defect arrival rate at a specific time of a software product. The function is given as;

$$f(t) = K \times (2t/c^2) \times e^{-(t/c)^2} \tag{1}$$

b) Cumulative Distribution Function : This gives estimation about the cumulative defect arrival rate at a specific time of a software product. The function is written as follows;

$$F(t) = K \times (1 - e^{-(t/c)^2}) \quad (2)$$

The parameter c, located in two functions of the Rayleigh Model, is related to the other parameter tmax which indicates the time when the Rayleigh curve reaches its peak. The relation between them is;

$$c = t_{max} \times \sqrt{2} \quad (3)$$

K is the total defect number of software product. F(t) shows the defect number at time t. The number of defects found at time t_{max} is equal to the 40% of total defects (Laird, 2006). The equation proves that claim is;

$$100 \times F(t_{max})/K = 100 \times (1 - e^{(-0.5)}) = 40\% \quad (4)$$

2.2 Linear Regression Model

The regression analysis model is one of the statistical models that indicate the relations between dependent and independent variables (Linear regression, n.d.). It estimates the value of the dependent variable with respect to the changes in the value of the independent variables. Regression analysis is using one or more independent variables to create a method and estimate the value of the dependent variable. If there is only one dependent variable, then the regression analysis method is called Simple Regression. The Simple Regression Method indicates the relationship between X and Y dimensions and the relation between them is plotted as a straight line. The Linear Regression Method is created to specify the straight line that fits most of the given set of points. This straight line method is estimated by finding the minimum length of a given set of points to decrease the prediction error rate. The equation expressing the line of the Linear Regression is;

$$y = a + bx \quad (5)$$

In which x is the explanatory variable; y is the dependent variable; b is the slope of the plotted straight line; a is the intercept and is equal to the value where x =0 in the given equation. The a and b values are estimated as follows with the given set of x and y values (Simple linear regression, n.d.);

$$b = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \quad (6)$$

$$a = \overline{y} - b\overline{x} \quad (7)$$

In this equation, the value of $\overline{x}$ is the mean of x value set and the value of $\overline{y}$ is the mean of y value set.

3 RELATED WORKS

The defect distribution pattern differs in each project in terms of the different project software development lifecycles. Each lifecycle applies different techniques and follows different steps to develop, test and maintain the software product. These differences affect the defect distribution pattern. The aim in the current study was to find a suitable model that reflects the defect distribution pattern of an iteratively developed software product. In order to do this, it is necessary to understand the nature of the iterative software development methodology. The defect arrival and removal processes are the processes through a software product′s lifecycle that help to gain an understanding of that system′s characteristics (Powell and Spanguolo, 2003). Thus, defects can be employed or injected into a software system to learn how that system behaves then; we can analyze and estimate the defect trends in order to also predict latent defect trends.

As every project has specific cases, we need to find a model that fits the best our projects to predict defect distribution (Koru and Liu, 2005). The developers of every project also have specific development styles. These individual development styles can affect the defect distribution of components, modules or projects, too. Therefore, a separate defect prediction model can be built for each developer. The study (Jiang et al., 2013) proposes to personalize each defect prediction process and build prediction models for every developer in a project.

In the literature, several models are presented that offer a best fit to defect distributions of software systems. These include; S-Shaped and Concave Shape models. The Linear Regression Model is also among these prediction models. One study (Bäumer et al., 2008) compares the Linear Model with Concave and S-Shaped models to show that the Linear Model also gives as good performance as the other software reliability growth models.

In another study (Abrahamsson et al., 2007), dynamic prediction models are constructed at the end of each iteration to predict the defects of the new iteration. The new prediction model is created using predictor values specific to that iteration and the previous iterations are given as an additional input. This feature gives the prediction model a dynamic characteristic. However, we choose to construct a prediction model using historical defect data belonging to completed modules of a project to model and observe the overall project level and module level defect trends.

Software Reliability Growth Models (SRGMs) are also used to estimate and predict the reliability of software products. The Rayleigh Model is one of the

SRGMs that are generally used to estimate the software project quality. This model presents equations to estimate these reliability measures. In literature, there are studies that use these equations to predict the number of defects (Vladu et al., 2011), defect density, defect removal effort and project release date (Qian et al., 2010).

COQUALMO is another estimation model that is presented in the literature (Hong et al., 2008; Madachy et al., 2010) and it can be used to predict the defect density of software products. However, COQUALMO needs information concerning the software product development phase and our defect data do not contain this information. There are few prediction studies in the literature that addresses this kind of lack of data. In this study, we present a prediction process that does not use project phase information, which is an important contribution of this study.

The models explained in this study use the historical defect density data of an iterative software project. As in study (Bäumer et al., 2008), we used Linear Regression Model and as in studies (Vladu et al., 2011; Qian et al., 2010), we used the Rayleigh Model to predict defect densities of latent defects. In the literature, there are not many studies that address the defect prediction process of an iterative software product. Furthermore, no study was found that analyzes both the module level and project level defect densities over iterations using the Linear and Rayleigh Models. This is the main contribution of the current study to the literature together with the sharing of our experience and the lessons learned.

4 CASE STUDY

This section describes the current study that analyzes the defect density distribution over iterations of an iterative, civil software project of a CMMI ML3 organization. Then, the constructed prediction Linear Regression Models and Rayleigh Models of module level and project level defect densities are explained.

4.1 Project Context

The project is an iterative, civil project and consisting of several modules developed over 3 years. There are several teams (containing 5 to 7 people) which are responsible for at least one of these modules. The whole project team consists of about 30 people and turnover of the team members has been low during the project.

Defects reported by the development team, test team and the project customers are saved in an issue tracker program. A reported defect is analyzed by the relevant team leader and assigned to one of the team members who will resolve it. The team member resolves the defect and then another team member, assigned by team leader, verifies that the defect has been resolved.

The project is developed based on subsequent releases. There are main and sub releases in project. Each main release developed over 4 to 6 weeks and follows the methodologies identified by the iterative software development. Thus, each main release is considered to be iteration. Main releases consist of sub releases that are generally developed over 5 to 7 days and released in the following order; after development of new requirements, after testing newly developed features and resolving the found defects through testing activities, after deploying and resolving the defects reported by customer. Therefore, with these activities through the sub releases, the needs of iterative development phases are fulfilled.

4.2 Measure Usability Assessment

Before generating the defect density prediction models for project under investigation, we assessed the usability of essential measures for prediction. We chose to predict the defect density of the project and verify that the constructed models generate good results. The defect density measure is a derived measure and generated from measures of the defect count and number of lines of code. To evaluate the usability of the defect density measure, we have to determine the usability of the base measure which are; the defect count and number of lines of code. To check the usability of these measures, we used Measure Usability Questionnaire (MUQ) (Tarhan and Demirörs, 2012). There are two kinds of MUQ for base measures and derived measures. The questionnaire consists of questions to evaluate the data availability and usability of measures. Due to the space constraint, the questionnaire cannot be provided here. However we should note that the information given in the completed questionnaires for the defect count, number of lines of code, and defect density indicated that the data for these measures fulfill the requirements of the measure usability. In particular, the data availability part of MUQ assists in the choice of suitable modules that can be used in the current study.

4.3 Observations on the Defect Distributions and the Specification of Research Questions

For the current study, to observe the defect density distributions, we analyzed defect densities at different levels of project, such as the module level and project level. As every level of project shows a different distribution pattern, we chose a model that fits best to each level. For this, we calculated defect densities and draw distributions over iterations.

At project level, we observed that, because of the nature of the iterative development, newly arriving requirements for each iteration cause the defect arrival rate to be stable. In other words, the defects occurring in any iteration generally stays at the same level. As a consequence, if we observe the cumulative defects over iterations, the defect distribution pattern seems to be a straight line. Hence, we chose to apply Simple Linear Regression Model to predict the defects for the new releases of the project. However, we also observed that, the defect density data shows a decrease in later releases. For this reason, we also analyzed the defect density of project with the cumulative Rayleigh distribution. In our study, the defect densities of 29 iterations were analyzed to predict the defect densities at project level.

Before determining the model to be used at module level, we analyzed the cumulative defect densities of 14 modules of the project. 10 of these 14 modules showed Rayleigh-like distribution and the other 4 modules showed S-shaped distribution. We did not choose an S-Shape model to predict the defect densities because the 4 modules were not completed and they have few data points. In other words, they show this S-Shaped pattern with a small number of iterations. On the other hand, the modules that have a Rayleigh-like pattern are generally completed or close to completion modules and have more data points. These modules show a Rayleigh distribution pattern because the modules are developed through releases and when the requirements for these modules are fulfilled, the defect arrival rate for each module decreases. Thus, the defect distribution of these modules over the iterations shows a different pattern from the defect distribution pattern of the overall project. So, for module level defect prediction, we chose Rayleigh Model. We also analyzed the module level defect densities with a Linear Regression Model to compare with the results from the Rayleigh Model prediction. The defect distributions of the three modules used in this study were analyzed through 15 iterations. These three modules were selected because they have same number of data points.

After determining the models that fit best the defect density distributions, we constructed the prediction models and tested the performance of these models. Our study was based on the following research questions:

1: What is the performance level of the Linear Regression Model in predicting the overall project defectiveness in iterative software development?

2: What is the performance level of the Rayleigh Model in predicting the overall project defectiveness through the iterations?

3: What is the performance level of the Linear Regression Model in predicting the module level defectiveness in iterative software development?

4: What is the performance level of the Rayleigh Model in predicting the module level defectiveness through the iterations?

4.4 Analysis Procedure

To construct the defect density prediction model, it is necessary to analyze the data and undertake various processes. To explain these processes, we create analysis procedures as stages. The stages for each model are given below.

In procedures, we use two parametric values. The parametric value n, in analysis procedures, is equal to the number of modules or projects that are used as training data of the models. In this study, we constructed models for 3 modules and a project, so for this study the value of n for modules is 3 and for the project is 1.

The value m in the Linear Model procedure is also parametric and this value is equal to the percentage of all the release numbers. For our study, the value of m is 70, which means the 70% of all releases will be used to train and construct the Linear Model at project level. The remainder of the defect densities of all releases, that means 30% of all releases, was used to test the performance of the constructed model.

The Rayleigh Model:

1) Gather the module or project length and defect data

2) For each release, calculate defect density by dividing the number of defects recorded in that period by module or project length

3) Depict the cumulative defect density against releases as Rayleigh curves

4) Estimate the K and tmax values of the Rayleigh Cumulative Distribution Function

5) Construct the Rayleigh Models for n number of modules or projects that are used for training

6) Estimate the mean K and tmax values of modules′ Rayleigh Models

7) Construct the Rayleigh Prediction Model

8) Predict defect densities and estimate performance of prediction results

The Linear Model:

1) Gather the module or project length and defect data

2) For project level, use m% of releases for the module level, use n number of modules to calculate defect density by dividing the number of defects recorded in that period by module or project length

3) Depict the cumulative defect density against releases; as data points

4) Estimate the a and b values of the Linear Regression Function

5) Construct the Linear Regression Prediction Model

6) Predict the defect densities and estimate performance of prediction results

4.5 Model Construction

4.5.1 Module Level Model Construction

Following the stages given in the analysis procedure, we constructed the Rayleigh Cumulative Distribution Function Models for three separate modules labeled M_1, M_2 and M_3. The defect density distributions of the modules show patterns like Rayleigh curve. While constructing the models, we calculated the value of K (total defect density) using the 40% principle (Laird, 2006). In other words, at time t_{max} where the defect density distribution reaches its peak, the found defect density equals 40% of total defect density. Table 1 shows the constructed Rayleigh CDF Model functions.

Table 1: Rayleigh Cumulative Distribution Functions of M_1, M_2, M_3 modules.

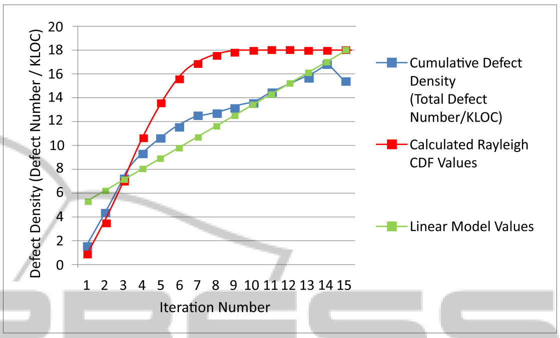
Module Name	Rayleigh CDF
M_1	$F(t) = 18.1 \times (1 - e^{-(t^2/18)})$
M_2	$F(t) = 13.53 \times (1 - e^{-(t^2/98)})$
M_3	$F(t) = 9.25 \times (1 - e^{-(t^2/72)})$

After constructing the Rayleigh Models of defect densities of modules M_1, M_2 and M_3, we also used these defect densities to construct Linear Models for these modules. The Linear Models for the M_1, M_2 and M_3 modules are constructed and tested for 15 releases or iterations. We used the Linear Regression Model equation given in section 2.2 to find the equation of these three modules′ Linear Model through 15 releases. Table 2 shows the equations of the constructed Linear Models of M_1, M_2 and M_3.

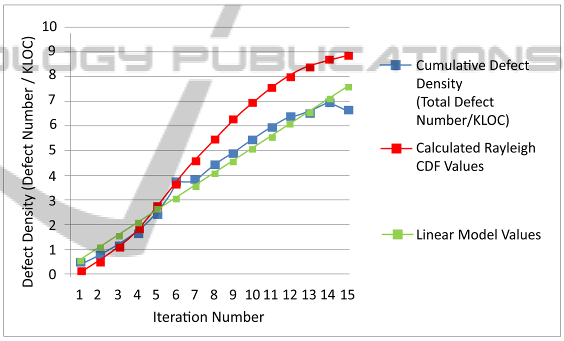
Figure 1 shows the distributions of actual and calculated (Rayleigh CDF Model and Linear Model) cumulative values of defect densities of each module through iterations 1 to 15.

Table 2: Linear Regression Functions of M_1, M_2, M_3 modules.

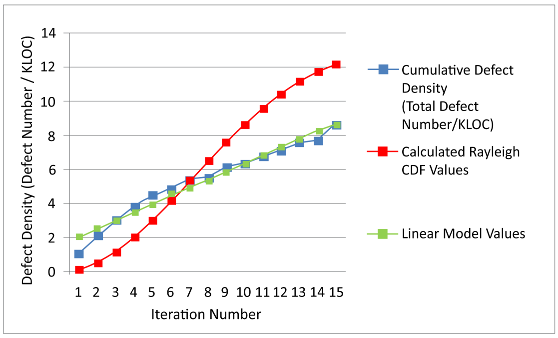
Module Name	Linear Model Equation
M_1	$y = 4.437 + 0.899x$
M_2	$y = 0.057 + 0.5x$
M_3	$y = 1.593 + 0.474x$



(a) M1 defect density distributions.



(b) M2 defect density distributions.



(c) M3 defect density distributions.

Figure 1: Module level defect density distributions.

4.5.2 Project Level Model Construction

After constructing the module level models, we used project level defect densities to construct a Linear Model and a Rayleigh Model. The Linear Model was constructed and tested for 29 releases or iterations. We split these releases′ defect density data into training and testing sets. 70% of 29 releases (20 releases) were used to construct the model and 30% of all these releases (9 releases) were used to test these models′ performances. As we calculated the K value of the module level Rayleigh Models, we calculated the K value of the project level Rayleigh Model using the 40% principal.

We also used the Linear Regression Model equation given in section 2.2 to find the equation for the Linear Model for the 20 releases. The equation of the constructed Rayleigh Model and Linear Model is given in Table 3.

Table 3: Project level model functions.

Model Name	Model Function Equation
Rayleigh CDF	$F(t) = 10.04 \times (1 - e^{-(t^2/128)})$
Linear Model	$y = 0.682 + 0.319x$

Figure 2 shows the distributions of the actual and calculated (Rayleigh CDF Model and Linear Model) cumulative values of the defect densities of project through iterations 1 to 20.

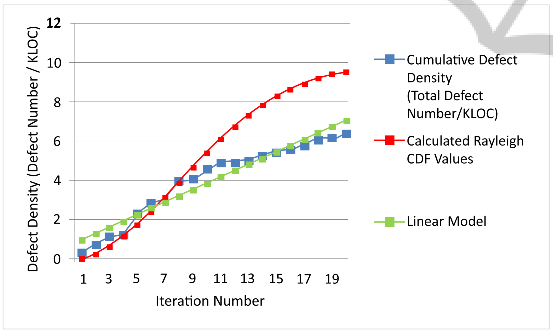


Figure 2: Project level defect density distributions.

4.6 Prediction Results

At the module level, we create Rayleigh CDF Models and equations of M_1, M_2 and M_3 modules with given equation in section 2.1. To create a prediction model and an equation for module level defect densities, we use the M_1, M_2 and M_3 modules′ Rayleigh CDF Models and equations, and we created another model by calculating the mean K and t_{max} values of Rayleigh CDF function. We used this newly constructed Rayleigh CDF Model to estimate and predict the defect density of another module, M_p and compared the predicted defect density result with actual defect density of M_p.

We also created a Linear Prediction Model using the linear functions of modules M_1, M_2 and M_3. For this, with using the linear function constants of modules M_1, M_2 and M_3, we calculated the mean a and b values of linear functions given in section 2.2. Table 4 presents information about Rayleigh CDF Prediction Model and Linear Prediction Model of module M_p.

Table 4: Model functions of M_p module.

Model Name	Model Function Equation
Rayleigh CDF	$F(t) = 13.63 \times (1 - e^{-(t^2/56)})$
Linear Model	$y = 2.027 + 0.624x$

After constructing the Linear and Rayleigh Prediction Models of module M_p, we calculated the cumulative defect densities of each iteration for module M_p using this prediction models. Figure 3 shows the actual and predicted defect density distributions through iterations 1-15.

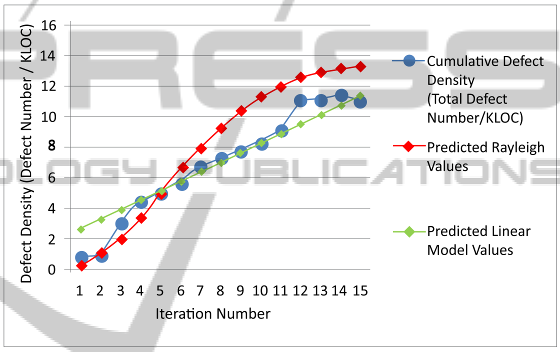


Figure 3: Module level defect density prediction model distributions.

After this stage, at project level, we created a Linear Model using defect densities of 20 releases (70% of 29 releases). We predicted the other defect densities of the 9 releases (30% of 29 releases) using the constructed Linear Model. We also predicted the defect densities of the 9 releases using the constructed Rayleigh Model for the project level defect densities as shown in Table 3. Figure 4 shows the additional defect density data points of the predicted and actual defect densities of the 9 releases.

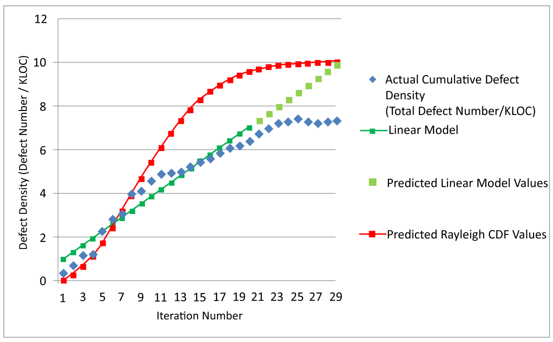


Figure 4: Project level defect density prediction model distributions.

The results show that the prediction models generally overestimate the defect densities. From this observation, it can be understood that the development team may work effectively in developing code with a low defect occurrence or they may remove defects without recording them; or the testing team does not test the projects effectively.

4.7 Prediction Performance Evaluation

Having constructed the Rayleigh and Linear Models to predict defect densities at module level and project level it was necessary to assess the prediction performance of the models to determine how well the models work. In literature, there are several measures that assess the performance of prediction models. We selected three measures to determine the goodness-of-fit; root mean square error (RMSE), mean absolute error (MAE) and mean magnitude relative error (MMRE). The RMSE measures the accuracy of the prediction model by measuring the average magnitude of the error (Eumetcal, 2011). It calculates the difference, in other word the residual, between the actual and predicted values and then, squares the difference. The square root of the residuals$'$ mean value gives the RMSE. The equation of RMSE is;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - f_i)^2}{n}} \qquad (8)$$

The MAE also measures the accuracy of prediction model by measuring the average magnitude of the errors (Eumetcal, 2011). The direction of errors is not important for the MAE. The result of the MAE shows how close the actual and predicted values are. We expected to see little difference between the RMSE and MAE values. This small difference between the RMSE and the MAE means that the variation of errors is also small. The equation of MAE is given as;

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - f_i| \qquad (9)$$

The MMRE also helps us to assess the performance of prediction models by evaluating how much the actual and predicted values differ relative to the actual values. The value of MMRE ≤ 0.25 shows that the prediction models$'$ performances are good (Kitchenham et al., 2001) and the models fit well. The equation of MMRE is;

$$MMRE = \frac{\sum_{i=1}^{n}\frac{|y_i - f_i|}{y_i}}{n} \qquad (10)$$

Table 5 shows the RMSE, MAE and MMRE values of the module level Rayleigh and Linear Models.

Table 5: Performance values of module level prediction models.

	Rayleigh Model	Linear Model
RMSE	1.777	0.969
MAE	1.515	0.664
MMRE	0.239	0.375

As shown in Table 5 the RMSE and MAE values of the Linear Model are lower than the values of Rayleigh Model. The difference between the RMSE and MAE values of both models are also small and this difference shows that how much the variations of errors are also small. However, although the Linear Model seems to have a better performance, the MMRE value of Linear Model is greater than the acceptable result of 0.25. For this reason, it is appropriate to use Rayleigh Model for module level defect density prediction.

Table 6 shows the RMSE, MAE and MMRE values of project level Rayleigh and Linear Models.

Table 6: Performance values of project level prediction models.

	Rayleigh Model	Linear Model
RMSE	2.707	1.592
MAE	2.413	1.434
MMRE	0.375	0.197

As shown in Table 6, at project level, the RMSE, MAE and MMRE values of the Linear Model are better than Rayleigh Model. The difference between the MAE and RMSE values of both Rayleigh and Linear Model is low which shows that the variations of errors are small. However, at project level, the MMRE value of the Rayleigh Model is greater than the MMRE value of the Linear Model and this value is also greater than the acceptable result of 0.25. For this reason, for defect density prediction at project level, the Linear Model is more suitable.

As we observe the results in both Table 5 and Table 6, the performance measure values for module level related to the RMSE and MAE values of both Linear and Rayleigh Models are lower than the values at project level.

At module level, with respect to the RMSE and MAE values, the Linear Model seems to have a better performance, but the MMRE value shows that the Rayleigh Model has more acceptable results. For this reason, the Rayleigh Model at module level is more usable. Modules are developed through releases and when the requirements for these modules fulfilled, the defect arrival rate for each module decreases. For this reason, the defect density distribution of these modules over the iterations shows a Rayleigh curve like pattern. To increase the performance of the Rayleigh Model at module level, we could use defect density data from more than three modules.

At project level, the reason why the Linear Model is better than Rayleigh Model is that the newly arriving requirements for each iteration result in a stable defect arrival rate and the defects occurring in any iteration generally remain at the same level. Thus, the distributions of cumulative defect densities over iterations converge to the Linear Model pattern.

4.8 Threats to Validity

It is important to examine the threats to the internal and external validity of any study.

Internal validity is one of the quality test criteria for a case study and it checks for the replicability of the proposed analyses (Yin, 2009). It also tests the situations that contain biases. The threats to internal validity of this study are as follows:

- Only the defect density data of one project was used, so we did not know whether the properties of the projects would affect our study therefore, we could analyze data from more projects.

- For prediction process of the module level defect densities, we used three modules however; we do not know the effect of other module properties on the proposed model. Thus, more modules could be analyzed, possibly with other types of prediction models to remove this threat.

- The MUQ was used to assess the usability of measures. The questionnaire helped us to decrease the subjectivity of this study and ensure that usable measures and data existed before constructing statistical prediction models. However, this assessment of usability requires a particular level of expertise about measurement, and still includes a degree of subjectivity.

- We specified the analysis procedures for both prediction models to ensure that our study had replicability. However, in order to use these procedures at organization level it is necessary to undertake more studies and improve our method.

Another quality test criteria is external validity which tests the generalizability of case studies (Yin, 2009). For the current study, we cannot ensure that these methods can be used in other contexts. Therefore, as a future work we can analyze the defect densities in relation to the properties of modules and projects. This data can also be analyzed using other prediction models.

5 LESSONS LEARNED

During our research, we encountered some challenges and we feel that the lessons we learned when resolving these problems can help researchers in their work concerning defect prediction process. First, to understand the nature of development and defect removal process of project, we spent much time considering the defect data. We drew the defect distributions of component level defects, release level defects, module level defects and project level defects. We distributed these defects over the development weeks or equally divided times such as periods of 5, 10, or 20 days. The component level and release level defect distributions generally had few data points if divided these defects over time into more data points, for some of the data points there are no defects and the actual nature of the defect distribution is lost. In our study, the components constitute modules and the modules constitute the project. To increase the data points and the number of defects correspond to these data points, we decided to use defect distributions of the modules and the project.

We discovered that in attempting to observe the defect distribution of development processes, however, the software development phase information (analyze, design, development, test or maintenance) of the defect, did not exist. This prevented us from analyzing the defect data according to the development phases. We cannot observe the influence of lower life-cycle phases′ quality onto the reached quality in upper-life cycle phases in software development process. Therefore, we learned that it is necessary to record the development phase data of that defect in iterative development as much as in waterfall development.

Then, we observed the defect removal effort distribution over time or releases. However, while assessing the measure usability of the defect removal effort, we observed that the majority of development teams do not enter the work log data of the defect removal effort. For this reason, we did not use effort data to construct a prediction model. The MUQ helped us to determine which measure was usable in prediction process. From the results of the questionnaire, we see that a number of defects and size of product were available, so it was decided to use defect density (number of defects / KLOC) to construct and analyze a prediction model. Difficulties were incurred when checking the release codes and counting the lines of module codes. Measuring the module sizes of final releases was easy but in previous releases, the code had not been grouped by modules or components. The classes of the components or modules in previous releases were located in different packages. This resulted in time being spent to find the classes of modules for the whole project. We found that the packaging of classes helps any member of staff to work more effectively. On the other hand, the project level product size was easily achieved, because at this level, the code size can be found by counting the lines of whole code.

Finally, the most significant step was deciding the most suitable prediction model. To determine which models that best fit our situation, we used defect density distributions and we observe that the module level defect density distribution curves converge to the Rayleigh curves and the project level defect density distribution curve converge to a straight line that shows a Simple Linear Regression.

6 CONCLUSIONS

In this study, we examined a defect prediction process of an iterative, civil project in which defect arrival phase data is not recorded. We analyzed the defect density data at module level and project level to predict the latent defect densities. By analyzing module level distributions; we were able to analyze defects in smaller code segments and by analyzing the project level distributions; we analyzed the defects in general. We used a software reliability growth model (SRGM), the Rayleigh Model and the Simple Linear Regression Model which need basic statistical and mathematical information. To predict the defect density of a module, we used the mean of three separate modules from the function coefficients from the Rayleigh Model and the Linear Model to create prediction model functions.

The results for the project level prediction show that the performance of the Linear Model is better than the performance of the Rayleigh Model. From these results, since the MMRE value of Linear Model was under 0.25, it can be seen that the Linear Model had a more acceptable performance. The result for the module level shows that performance of the Linear Model is better than the Rayleigh Model with respect to RMSE and MAE values. However, the MMRE value of the Linear Model does not have an acceptable performance value (it should be less than 0.25). The MMRE value of Rayleigh Model has a suitable value which is smaller than the acceptable result of 0.25.

The modules used to construct a prediction model have different complexities. So, we can increase the performance of module level prediction results by increasing the number of modules that are investigated. At project level, due the nature of iterative development, the defect arrival rate generally remains at the same level and the distribution of the defect densities converge to a Linear Model. Therefore, the Linear Model has a higher performance than the Rayleigh Model.

The most important lessons learned from this study are observing the nature of defect distributions, identifying and overcoming the lack of data, and deciding the most suitable prediction model that fits best to the situation. Defect arrival and removal data collection is important to model defect arrival and removal patterns in relation to project phases. Due to the nature of iterative development, a defect found in an iteration can be fixed in another iteration. It is very important to specify in which release the defect is found and in which release the defect is fixed. Another important issue is the consistency and integrity of project planning data with project defect data. Defect tracking tool should be capable of accessing and working integrated with project management tool.

For future work, we are planning to include data from more modules and projects in the models and examine the prediction of the project schedule using the defect removal effort spent by the project staff.

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