A SOFTWARE BENCHMARKING METHODOLOGY FOR EFFORT ESTIMATION

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Submitted by **Mina Nabi** in partial fulfillment of the requirements for the degree of **Master of Science in Information Systems, Middle East Technical University** by,

Prof. Dr. Nazife Baykal ______________________
Director, **Informatics Institute**

Prof. Dr. Yasemin Yardımcı Çetin ______________________
Head of Department, **Information Systems**

Prof. Dr.   Onur Demirörs ______________________
Supervisor, **Information Systems, METU**

Examining Committee Members:

Prof. Dr. Semih Bilgen ______________________
EEE, METU

Prof. Dr. Onur Demirörs ______________________
IS, METU

Dr. Ali Arifoğlu ______________________
IS, METU

Assist. Prof. Dr. Banu Günel ______________________
IS, METU

Assoc. Prof. Dr. Altan Koçyiğit ______________________
IS, METU

Date: 14.09.2012

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Name, Last name: Mina Nabi

Signature: _________________

ABSTRACT

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FOR EFFORT ESTIMATION

Nabi, Mina
M.Sc., Department of Information Systems
Supervisor: Prof. Dr. Onur DEMİRÖRS

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Software project managers usually use benchmarking repositories to estimate effort, cost, and duration of the software development which will be used to appropriately plan, monitor and control the project activities. In addition, precision of benchmarking repositories is a critical factor in software effort estimation process which plays subsequently a critical role in the success of the software development project. In order to construct such a precise benchmarking data repository, it is important to have defined benchmarking data attributes and data characteristics and to have collected project data accordingly. On the other hand, studies show that data characteristics of benchmark data sets have impact on generalizing the studies which are based on using these datasets. Quality of data repository is not only depended on quality of collected data, but also it is related to how these data are collected.

In this thesis, a benchmarking methodology is proposed for organizations to collect benchmarking data for effort estimation purposes. This methodology consists of three main components: benchmarking measures, benchmarking data collection processes, and benchmarking data collection tool. In this approach results of previous studies from the literature were used too. In order to verify and validate the methodology project data were collected in two middle size software organizations and one small size organization by using automated benchmarking data collection tool. Also, effort estimation models were constructed and evaluated for these projects data and impact of different characteristics of the projects was inspected in effort estimation models.

Keywords: Benchmarking methodology, benchmarking data, Effort Estimation Models, Functional Similarity

ÖZ

İŞ GÜCÜ KESTİRİMİ İÇİN BİR YAZILIM REFERANS
VERİ KÜMESİ YÖNTEMİ

Nabi, Mina
M.Sc., Department of Information Systems
Supervisor: Prof. Dr. Onur DEMİRÖRS

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Yazılım proje yöneticileri genellikle iş gücü, maliyet ve yazılım geliştirme süresini tahmin etmek için referans veri kümelerini kullanırlar. Bu tahminler proje faaliyetlerinin uygun planlama, izleme, ve kontrolü için kullanılır. İş gücü kestirimi yazılım geliştirme projesinin başarısında önemli bir rol oynamaktadır ve referans veri kümesinin kalitesi yazılım proje iş gücü kestirim sürecinde kritik bir faktördür. Güvenilir bir referans veri kümesi oluşturmak amacıyla, kestirim veri niteliklerinin ve veri özelliklerinin tanımlı olması önemlidir. Öte yandan, çalışmalar referans veri kümelerinin veri özellikleri bu veri kümelerine dayalı çalışmaların yaygınlaştırılması üzerinde etkili olduğunu göstermektedir. Referans veri kümelerin kalitesi sadece toplanan veri niteliğine bağlı değildir, aynı zamanda bu verilerin nasıl toplandığıyla da ilgilidir.

Bu tezde, organizasyonlarda iş gücü kestirim amacıyla referans veri kümesine veri toplamak için bir metodoloji önerilmiştir. Bu metodoloji, üç ana bölümden oluşmuştur: referans veri kümesinin ölçüleri, referans veri kümesinin veri toplama süreçleri, referans veri kümesi için veri toplama aracı. Bu yaklaşımda literatürde önceki çalışmaların sonuçlarından da yararlanılmıştır. Metodolojiyi doğrulamak ve geçerlemek amacıyla, iki orta boy yazılım organizasyonundan proje verileri otomatik referans veri kümesi veri toplama aracını kullanarak toplandı. Ayrıca, iş gücü kestirim modelleri oluşturuldu ve bu projelerin verileri ve projelerin farklı özelliklerinin etkisi iş gücü kestirimi için değerlendirildi.

Anahtar Kelimeler: Referans Veri Kümesi Oluşturma Metodolojisi (Benchmarking Metodolojisi), Referans Veri , İş Gücü Kestirim Modeli, Fonksiyonel Benzerlik.

To My Family

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LIST OF ABBREVIATIONS AND ACRONYMS

ARIS	: Architecture of Integrated Information Systems
BFC	: Base Functional Component
COSMIC	: The Common Software Measurement International Consortium
CSBSG	: Chinese Software Benchmarking Standards Group
EPC	: Event-driven Process Chain
FSM	: Functional Size Measurement
GUI	: Graphical User Interface
IPA/SEC	: Information-Technology Promotion Agency/Software Engineering Center
ISBSG	: International Software Benchmarking Research Group
LOC	: Line of Code
MMRE	: Mean Magnitude of Relative Error
MRE	: Magnitude of Relative Error
PRED	: Prediction Level Parameter
PROMISE	: Predictor Models in Software Engineering
SLOC	: Source Line of Code
SRS	: Software Requirement Specification
WBS	: Work Breakdown Structure

CHAPTER 1

INTRODUCTION

1.1. Background of the problem

For software organizations it is important to deliver a software product on time within expected quality to their customers. For the purpose of allocating appropriate resource and making reasonable schedule in project planning phase, reliable and accurate effort estimation is important (Huang & Chiu, 2006). Software effort estimation is crucial input for monitoring and controlling the allocated resources during project management activities. Also, the accuracy of the development effort estimation plays an important role in success of the maintenance activities in the software development of the project (Huang, Chiu, & Liu, 2008).

Many effort estimation methods have been suggested by researchers during the last decade. Among these methods estimation by expert judgment, analogy based estimation, and parametric (algorithmic) estimation are widely used (Huang & Chiu, 2006), (Huang, et al., 2008), (Mendes, 2009). Expert estimation is an estimation method which is conducted by a person who is expert in the task. In this estimation method expert follows a non-explicit and non-recoverable process to estimate required development effort (Jorgenson & Sjoberg, 2004). In analogy based estimation similar projects to the one to be estimated are found from historical data and then estimation is derived from the valued of selected projects (Jorgenson, Indahl, & Sjoberg 2003). Algorithmic effort estimation methods are based on using statistical analysis to predicate the effort estimation equations. Constructive cost model (COCOMO), and ordinary least square (OLS) regression model are most commonly used methods among the parametric effort estimation techniques (Kaczmarek & Kucharski, 2004), (Huang et al., 2008). All of these estimation models rely on historical (benchmarking) datasets. Benchmarking dataset is reference for making decision in start phase of the project, and in order to establish a reliable estimation model and predicting required effort and cost, accurate and sufficient historical project data are needed. Since new software organizations do not have enough project data and also most of the organizations ignore the need for data collection, there is a strong need for external benchmark datasets. International Software Benchmarking Standards Group (ISBSG) dataset (2007), Chinese Software Benchmarking Standards Group (CSBSG) dataset (2006), Information Technology Promotion Agency (IPA/SEC) dataset (2004), Predictor Models in Software Engineering (PROMISE) Dataset (2008), Laturi/Finnish software metrics association (FISMA) Experience dataset (2009) are common datasets provided by research groups for this propose.

Benchmarking process is defined by Bundschuh and Dekkers (2008) as the process of identifying and using knowledge of best practices to improve in any given business, also the most important point is that benchmarking is not a standalone action. It is also defined by Dekkers (2007) as a continuous and repeatable process of measuring and comparing with other best practices. Benchmarking can be distinguished as internal and external benchmarking. In internal benchmarking the comparison takes place with projects which belong to the same or a different enterprise. But in contrast, external benchmarking cope with market-related comparisons, and its data is from outside of the organization (Bundschuh & Dekkers 2008). A secondary classification of benchmarking is based on the availability of the dataset. The dataset can be public, semi-public or private benchmark repository. When the data itself is available like data in ISBSG (2007) it is called public. In other cases the data is not available but the analysis results are open to the public as IPA/SEC (2004) dataset it is semi-public. Finally, it is private when the repository is not accessible since the data is integrated within a software estimation tool as in SPR (2010).

1.2. Statement of the Problem

Researches show that data characteristics of benchmark data sets have impact on studies based on using these datasets. Unfair and unbalanced datasets have potential effects on the performance of effort estimation techniques, and these problems in the datasets raise threats in generalizing the effort estimation techniques, algorithms and tools used by these methods (Bachmann & Bernstein, 2010), (Bachmann & Bernstein, 2009). Accurate benchmark data repository is a crucial key factor for improving accuracy of effort estimation. Many studies have been conducted to propose effective effort estimation methods, but in those studies distribution of the historical data, which has a impact on effort estimation accuracy, have not been considered (Seo, Yoon, & Bae, 2009). So the inaccuracy and noise in benchmark data repository is an important problem which should be considered.

Benchmarking data repositories suffer from some problems: collection of the data are expensive and difficult; they are limited in collected project numbers, outliers in the dataset can have misleading influence in the estimation result, academics have limited access to industrial project datasets, and finally the missing data is significant in the datasets. Also in order to validate these data sets, the correlation among the variables should be considered. When for example 10 variables are measured, 45 correlations should be considered. Obviously, by increasing the number of variables, the number of correlations rises rapidly and the systematically large correlation metrics are needed (Liu & Mintram, 2006). Another problem of benchmark datasets is that, there is low rate data submission in software industry and because of the lack of publicly available benchmarking datasets and limitation of their size, effort estimation models cannot be validated truly (Cukic, 2005).

On the other hand, number of data attributes collected in multi organizational benchmarking data set is high, for example in ISBSG version 11 there are 118 attributes, and the task of collecting such a number of attribute is not possible. So, the number of missing data is high in these data repositories. As it is mentioned missing data influences the accuracy of estimated effort. Furthermore, some of the techniques for imputation of these missing data results in loss of data and subsequently inaccurate estimation (Sentas & Angelis, 2006). On the other hand software repositories contain heterogeneous project data, so parametric effort estimation methods encounter with poor adjustment and predictive accuracy. So, heterogeneity is another problem of data repositories (Cuadrado, Rodriguez, Sicilia, Rubio, & Crespo, 2007) (Huang et al., 2008). Unbalanced data also have impact on the accuracy of effort estimation methods, and it imposes a validity threat to the validation of effort estimation techniques (Bachmann & Bernstein, 2010).

Researchers propose to use single company data repository, rather than cross company data repository. The studies show that benchmarking using single company dataset produces more accurate data in comparison to multi-company dataset, but organizations face three problems when using within company project data: the time required for collecting data from a single company can be excessively high, technologies used in the company can change and older projects will not be representative any more for new projects, and data care is needed to guaranty the consistency of the dataset. So, many organizations tend to use cross company datasets, which on the other hand suffers from other problems: again care for keeping consistency of dataset is needed, and difference in process and used technologies of different companies may cause trend through different companies (Mendes, Lokan, Harrison, & Triggs, 2005), (Mendes & Lokan, 2007). In cross company benchmarking data set project data is collected from different companies with different application domains and technologies. Since mostly large scale companies contribute in this process, the sample in these data sets is not random and not representative, as in CSBSG dataset (Wang, Wang, & Zhang, 2008). Therefore these data sets cannot result in accurate estimation.

In addition, there is not an international standard for developing benchmark dataset, and different repositories are developed in different countries which include different attributes and categories. Thus, mapping between attributes of diverse data repositories is not possible, and estimation result from different repositories cannot be compared to verify and generalize the findings (Gencel, Buglione, & Abran, 2009).

1.3. The Purpose and Scope of the Study

The purpose of this study is to develop an approach for data collection which includes meta-data model of project attributes for benchmark data repository, data collection process, and tool support for data collection according to defined benchmarking attributes and processes. Firstly, in this study the characteristics of available benchmark data sets were evaluated and the core factor drivers of effort estimation were identified. Also, a survey was performed in the literature for finding benchmarking attributes. In order to define a data model with correct and not noisy data, project attributes was categorized as core project attributes and extended project attributes. Core project attributes are sufficient for an accurate and reliable estimation, and meanwhile the extended attributes elaborate more precise characteristics of software business domain. In this case, data collection process will be more precise from viewpoint of completeness and high fill in ratio.

Secondly, previously defined benchmarking data collection processes were refined for automation purpose. Implementation of collecting benchmarking dataset was the next target of this study. This automated benchmarking data collection tool with considering defined benchmarking methodology and data collection processes will ease the data collection process.

1.4. Significance of the Study

One important reason for this study is that current external benchmark datasets include missing and noisy data, and they contain heterogeneous project data. Existence of such noisy data leads to inaccuracy in effort estimation methods. Meanwhile, the number of attributes in these benchmark datasets is too much hence it is difficult for data provider to submit all these attributes, so this phenomena lead to constructing benchmark dataset with missing and dirty data. In this study by proposing meta-model key project attributes will be determined and by eliminating unnecessary attributes more accurate data without noise will be collected from providers. The core project attributes will guarantee reliable effort drivers to estimate the required development effort. On the other hand, by integrating defined benchmarking attributes, benchmarking data collection processes, and tool support it will be a substantial improvement for constructing benchmarking data repository.

In addition, tool support will be very useful in decreasing consumed time and effort for data collection and it will be efficient for the usage of accurate effort estimation in project management. Also, since it can be customized within organizations it will be a useful tool in benchmarking data collection for organizations.

1.5. Research Questions

In order to overcome the problems described in the "Purpose of the Study" section, these research questions will be explored:

Q1: What are project attributes of a benchmarking meta-model which can be used in establishing reliable effort estimation models?

Q2: For the purpose of software benchmarking which measures can be collected in organizations in practice?

Q3: What are the requirements of automated benchmarking data collection processes which improves benchmarking data repositories?

Q4: Is this benchmarking methodology applicable to other organizations?

Q5: Does data collected by this methodology lead to better effort estimation?

1.6. Road Map

In chapter 2, a review of relevant literature on benchmarking, effort estimation models are described.

In chapter 3, proposed benchmarking methodology is described in detail. It includes three subsections: benchmarking measures, benchmarking data collection processes, and benchmarking data collection tool Cubit (http://smrg.ii.metu.edu.tr/cubit/). As an attachment to this chapter, refined benchmarking data collection processes are given in APPENDIX.

In chapter 4, the implementation of the approach which is used in this study and its design is described. The chapter describes two case studies conducted in this thesis; the explanatory case study, and the validation case study.

In chapter 5, conclusions and contributions of this research are presented briefly, and suggestions for future work are made.

CHAPTER 2

BACKGROUND AND RELATED RESEARCH

2.1. Synthesis of the Literature

The word “benchmark” has been used in the past in different ways. One of the usages of this word is the ability of a software organization to determine the competitiveness in a given business area, and required productivity improvement for sustaining a specific business. From this viewpoint benchmarking is a data intensive process, which means for benchmarking it is necessary to have a benchmarking database. Such a database contains performance measures and other characteristics for a set of projects. Then similar projects will be found and performance of these projects will be compared with the target project (Beitz & Wieczorek, 2000).

According to Meli (1998) a benchmarking dataset is a collection of technical and management data for the software to develop forecasts for the future and evaluation of the productivity of present project. They contain actual and anticipated data of projects for organizations, and they are collected according to proven security and refinement model. For benchmarking the dataset can be filtered by similar projects, then the selected projects data can be analyzed individually or by respect to statistical dispersion and correlation indicators.

2.1.1. Data repository and accuracy of data repository

The quality of a benchmark data set is relative to the quality of the data in the data set. There are studies which evaluated the data quality of the benchmark data. Herzog (2007) suggested most seven cited properties of quality as (1) relevance, (2) accuracy, (3) timeliness, (4) accessibility and clarity of results, (5) comparability, (6) coherence, and (7) completeness. Liebchen and Shepperd (2008) examined the quality of the data with accuracy and noise of the data with objective of assessing the techniques used in quality management of software engineering. Noise was described as incorrect and inaccurate data. They evaluated the studies which address the accuracy of data in datasets. Surprisingly they observed that only the total of 23 studies directly address this problem at that time, and in comparison to other empirically based disciplines it is not studied enough. Among these studies 73% of the evaluated articles claimed data noise is a significant problem. Empirical analysts address this problem by the approach of manual inspection and prevention techniques such as tool support for data collection.

Data values can be absent from a benchmark data repository because of various reasons, like inability to measure a specific benchmark attribute. Many research for handling missing data have been done. A comprehensive experimental analysis of five techniques of handling and imputation of missing data which were conducted by Van Hulse and Khoshgoftaar (2007) is one of these studies. Deleting data from a dataset can cause in loss of potentially valuable data. In this study also impact of noise on the imputation process were examined and high impact of noisy data on the effectiveness of imputation techniques observed. Bayesian multiple imputation and regression imputation reported as most effective techniques, and mean imputation reported as extremely poor performance technique.

Strike, Emam, and Madhavji (2001) also performed a comprehensive simulation to evaluate the techniques for dealing with missing data in software cost estimation modeling. Three techniques of listwise deletion, mean imputation, and eight different of hot-deck imputation were assessed in this study. They observed that all these techniques are well performed, and they suggested listwise deletion as reasonable choice. But they also state that this technique does not provide best performance necessarily, so using hot-deck imputation suggested as a method which produce best performance with minimal bias and highest precision.

Similarly, Sentas and Angelis (2006) conducted a comparative study on missing data techniques (multinomial logistic regression (MLR), list wise deletion (LD), mean imputation (MI), expectation maximization, and regression imputation) and suggested multinomial logistic regression (MLR) for using imputation on databases with missing data. In this experimental research, ISBSG version 7 was used, which contained 1238 projects information at that time. Since they want to observe the difference in efficiency of these MLR methods, they first selected projects which have complete data with no missing values. They resulted in 166 project data. Then by using three different mechanisms they create missing data. These mechanisms were: missing completely at random (MCAR), non-ignorable missingness (NIM), and missing at random (MAR). For analyzing the difference between missing data techniques, analysis of variance (ANOVA) was used. This statistical method was applied by using SPSS program. The results show that in small percentage of missing data, the purposed method (MLR) gives satisfactory results like other methods, but in high percentage of missing data it performs better than other methods. Although LD approach is more used as missing data imputation techniques, but the loss of precision and bias are major problems of this method. Determining when LD method is unsuitable method, problem of missing data from other aspects is stated as future work in this paper.

Moses and Farrow (2005) also used Bayesian statistical simulation program BUGS to impute missing data. The ISBSG Data Repository (2003) is analyzed, and used for reexamining a statistical model for work effort. Different distributions were used to model missing data: categorical distribution applied to language type (LT), imputation regressions used for imputing maximum team size (MTS), and also Gamma distribution used for imputing MTS. Differences between 2 and 4GLs, 3 and 4GLs, APG and 4GLs, 5 and 4GLs, 3GLs and APGs were observed. Imputing MTS for missing data revealed differences in required effort for development of systems with different LDs, and development types. After imputation the author observed that the model derived from this model imputation is likely to be useful than model which using deletion strategy.

There are also studies which evaluate the benchmark data repository, and possible improvement in data repositories. Gencel, Buglione, and Abran (2009) mentioned some reasons which cause disagreement in relating effort and cost drivers. Not existing an international standard for creating benchmarking data repository and difficulty in mapping attributes of different repository, are stated as a major problem. Improvements opportunities for benchmarking and using benchmarking repositories are suggested in this paper. Developing a standard definition and categorizing benchmarking attributes which are used in data repositories, is one of important improvement opportunities mentioned here, and supported by giving examples from ISBDG data repository. This allows benchmarking repositories to be unified and mapped to an internationally accepted standard. Another improvement suggestion for data repositories stated as reporting effort and duration based on software development life cycle phases. An improvement and refining way of classifying the application types in software engineering based on classifications in civil engineering and two software practice standards of ISO 12182 and ISO 14143-5 has purposed too.

Distribution of benchmark data is an important issue which influences the accuracy of software effort estimation. Seo, Yoon, and Bae (2009) proposed a data partitioning model by using Magnitude of Relative Error (MRE) and Magnitude of Error Relative (MER) values which subsequently will improve the weak points of effort estimation models based on least square regression (LSR). They stated that MRE and MER are usually used in effort estimation accuracy measurement by considering deviation of data point from LSR. The authors conducted an empirical experimental study by using two industry data sets: ISBSG Release 9 and a bank data set which consists of project data from a bank in Korea. In this experimentation by comparison between estimation accuracy of a single LSR without using partitioning, and LSR with data partitioning using fuzzy clustering and also proposed partitioning approach, an improvement in software effort estimation observed. Also the boundary values for MRE and MER were proposed to be between 0.1 and 0.5 which can ensure better effort estimation accuracy.

In another study an estimation process proposed by Cuadrado et al. (2007) for improving predictive accuracy of datasets and overcoming the problem of heterogeneous projects data in data set. One possible way of overcoming to the problem of such datasets was proposed to use mathematical equations derived from partitioning dataset according to different parameters and subsequently clustering these partitions for finding more accurate model. They used ISBSG release 8 for validating proposed process. The steps of proposed effort estimation process were: first according to importance of attributes data repository were divided to partitions, then by using EM algorithm partitions were clustered, then for each cluster regression equation was calculated, and finally in order to perfume new estimation according to available data a regression equation should be selected. In addition, in this study a tool support for effort estimation was presented to facilitate the estimation process.

However in another study Huang et al. (2008) investigated the accuracy of the effort estimation models which are derived from data clustered by diverse effort drivers. Ordinary least square (OLS) regression method, which is a popular method in creating software effort estimation models, is used to establish effort estimation model in each dataset clustered by effort derivers. Next, difference of accuracy in effort estimates are compared between clustered and not clustered data. In this research Pearson Correlation, and one way ANOVA were used to identify the effort drives for utilizing in software estimation model. Then, k-means and Scheffe's method are used to cluster effort drivers which obtained from previous stage. After clustering effort drivers, by using OLS method, effort estimation model was established for each group. ISBSG repository version 7 was used in this study. Projects with quality rating "C" and "D" were excluded from the study, and data which had International Function Point User Group (IFPUG) counting approach are selected. Among these selected data there were projects with missing data, after excluding them a remaining 171 projects were selected to be used in this research. They selected six effort drivers as function points (FP), max team size (MTS), development type (DT), development platform (DP), language type (LT), and methodology acquired (MA). The results of their study show that software effort estimation models based on homogeneous and inhomogeneous datasets do not differ in producing accurate effort estimates.

The impact of development type, and used language as project factors are examined by Moses, Farrow, Parrington, and Smith (2006) on effort estimation and productivity. The aim of this study was to provide a comparison of productivity rates of a company with productivity rates of international data repositories. In this study, projects data of ISBSG (2003) data repository and projects data used in Reifer in a paper were used. In Reifer's paper 500 projects from 38 organizations are utilized. They examined three productivity measures: Hours per Line of Code HR/SLOC, Source Lines of Code per Staff month SLOC/SM, and Hours per Function Points

HR/FP. This study showed that the productivity rate for the studied company is higher than ISBSG and Reifer Consultants Incorporated data repository. The reasons behind this outperforming are indicated by several factors. Firstly, in the company projects were led by company staff that had wide company knowledge of both systems and business processes. Secondly, the company had an optimized development process, and those activities which do not add any value were eliminated from development process of the company. Thirdly, the company is data model driven and it supports Rapid Application development and reuse code. Lastly, in this company a programming language and a DBMS were used for developing which developers had several years of experience in them within the organization. The study shows that ignoring projects data can result in inaccurate productivity rates.

2.1.2. Developed estimation models and improvement opportunities for effort estimation

Many effort estimation models have been suggested by researchers based on using benchmark data repositories. There are many studies which evaluate the accuracy of these methods. Jeffery, Ruhe, and Wieczorek (2000) investigated accuracy difference between two estimation models of ordinary least squares (OLS) regression as parametric technique and analogy-based estimation as non-parametric technique. They used magnitude of relative error (MRE) for evaluation of estimation models. Also, the difference of estimation accuracy between estimation derived from multi-company data and company-specific data is explored. They used multi organization data of ISBSG and compared the accuracy results of estimation with the results of using company-specific data from an Australian company which at that time did not contribute to ISBSG data repository. As a result they observed that estimation accuracy in estimates using company specific data is higher than estimates using the ISBSG data repository. They observed that in using company data both OLS regression and analogy can be considered, but in using ISBSG data set for a non-contributing company OLS regression should be considered rather than analogy based estimation.

Neural networks are one of software effort estimation methods which are often selected because of their capability to approximate any continuous function with arbitrary accuracy. Setiono, Dejaeger, Verbeke, Martens, and Baesens (2010) applied a comprehensible if-then rules derived from neural networks trainings in software effort estimation based on rule extraction method. For validating this proposed method, they used ISBSG release 11. They compared the neural network extraction algorithm with three other methods: ordinary least square (OLS) regression, radial basis function networks, and Classification and Regression Trees (CART). They observed that CART method results in most accurate estimations, but because of CART tree size the obtained model did not have comprehensibility. The authors stated that, by considering comprehensibility, the neural network by role extraction is more suitable for effort estimation.

In another study Liu, Qin, Mintram, and Ross (2008) applied the framework which has been proposed by Liu and Mintram in 2005 to ISBSG data repository release 9 to with the purpose of demonstrating practical utility of this framework. This framework applies statistical analysis to a publicity dataset, in order to remove outlier variables and identify the dominate variables. As evaluation metrics they used Mean Magnitude of Relative Error (MMRE), Median of Magnitude of Relative Error (MdMRE), balanced MMRE (BMMRE), Magnitude of Error Relative (MER), mean MER (MMER), median of MER (MdMER), and prediction at level 1. They results show that removing outliers, and removing inter-correlated predictor variables will improve accuracy of effort estimation. Also, they came up with conclusions: a few variables in this case study contributed the most effort prediction, and the models using parametric techniques (ordinary least squares regression and Robust Regression Model) have estimation accuracy higher than non-parametric techniques.

Bourque, Oligny, Abran, and Fournier (2007) proposed a model for software engineering project duration based on project effort. They used ISBSG data repository fourth release for their analysis. Models for developed projects for personal computer, midrange, mainframe platforms, and for entire project types are created. Also different models are built for projects with required effort fewer and more than 400 person-hours. Meanwhile, investigating was conducted to opportunity of constructing model directly from project functional size, and results revealed that estimation can be derived from project size, and also it gives better estimation. Lastly, the impact of maximum number of resources on duration of project was examined, and using this attribute increased 10% more duration variance. Observations showed that relation between effort and duration of project is not linear, and there is an exponential in the range of 0.3 and 0.4. The developed models show that "first order" estimation from effort values can be used for estimating duration of the project.

On the other hand, different techniques have been utilized for improvement of effort estimation models. Huang and Chiu (2006) investigated the appropriate weighted similarity measures for each effort drivers in analogy based effort estimation model by using genetic algorithm in order to observe improvement on effort estimation accuracy. Three different analogy methods which studied in this paper are: unequally weighted, linearly weighted, and nonlinearly weighted methods. ISBSG dataset release 8 and IBM DP services databases are used to in experimental study. They observed that the weighted analogy methods generated higher software effort estimation accuracy rather than traditional unweighted approach, and this demonstrates that using genetic algorithm for finding weights for effort derives provide better results in compare to subjective weights assigned by experts.

Software engineering research community presented many models for effort estimation which function point (FP) is one of them. FP method is a useful software estimation methodology to improving project estimation accuracy. A study was conducted by Ahmed, Salah, Serhani, and Khalil (2008) to adjusting the complexity weight metric of function point (FP). In order to adjust the complexity weight metrics of FP, genetic algorithm based approach is used. They consider a chromosome as a vector of real parameters, and a gene as a real number representing one FP complexity weight. They also used 40% two-cut point, 20% uniform, and 20% arithmetic crossover operations by 0.7 probabilities, and random mutation operation by 0.2 probabilities to find better results. They used MMRE as fitness function in their genetic algorithm. Also, ISBSG data repository release 9 was used in this research, and they selected 600 data from ISBSG by considering quality rating of "A" and "B" and also new development projects with IFPUG counting approach. As a result, by using information and integration of past projects FP structural elements and using genetic algorithm, they observed an average of 50% improvement in MMRE.

Lokan and Mendes (2009) investigated the difference of effort estimation accuracy between project by project split and date based split against each other. Accordingly, by considering project by project chronological splitting and date based splitting, and using multivariate regression estimation models were built, and evaluated using training set (from which the model is built) and testing set (which the model accuracy is assessed). ISBSG release 10 is used in this study, which contained 4106 projects. They excluded projects with quality rating not equal to "A" and "B", and projects with measurement approach not equal to IFPUG. They also excluded projects which their unadjusted function points, and development team effort are unknown, and projects which had extremely influential, so they come up with 906 projects. As a result they stated in their study, estimation accuracy using a simple date based split seems to be the same as estimation accuracy sing a project by project split. But because of the threats to validity which they stated themselves (ISBSG is not a random sample project, and assumptions they take in order to build models automatically, and not stabling their results) they didn't generalize their findings, and they stated it needs further study.

In most effort estimation researches all assumptions are on the fact that software size is a primary predictor, so it should not be underestimated. So, Gencel and Demirors (2008) revisit the function size measurement (FSM) methods in order to find improvement opportunity for FSM, and subsequently improvement in benchmarking and effort estimation. They used International Software Benchmarking Standards Group (ISBSG) for their empirical study. Among their findings, the convertibility of size among different functional size methods, considering the target functional domain type of FSM methods, developing methods for size estimation in earlier stages of life cycle before availability of FURs, and convertibility of size for later phases in life cycle are more effective in later effort estimation improvements.

There are many studies which investigate new size estimation techniques and effort estimation models to improve effort estimation accuracy, but a few of studies pay attention to quality of historical data which were used in constructing estimation models (Tunalilar, S., 2011). Tunalilar (2011) proposed an effort estimation methodology for organization in order to manage effort estimation processes within the organizations. In this methodology, all necessary steps of effort estimation processes are defined which include data collection, size measurement, data analysis, calibration, effort estimation processes. Also, effect of functional similarity, and application domain of project are investigated in this study. The results of this study showed that considering functional similarity, a Base Functional Components (BFC), and classifying projects by application domains of them improve correlation between effort and size.

CHAPTER 3

SOFTWARE BENCHMARKING APPROACH FOR EFFORT ESTIMATION

In this chapter a software benchmarking methodology is proposed for effort estimation. This approach consists of three parts; benchmarking measures, benchmarking data collection processes, and benchmarking tool. In the section 3.1 of this chapter benchmarking measures are explained in detail. In the section 3.2, benchmarking processes are introduced. Finally, section 3.3 presents the developed benchmarking tool for automating the methodology.

3.1. Benchmarking Measures

There are many benchmarking measures which are collected in benchmarking data repositories. However in most of the organizations projects data is not kept in such a detail and this leads to sparseness of the benchmarking data repositories. As discussed earlier in the literature review, although International Software Benchmarking Standards Group (ISBSG) initiated benchmarking standardization studies in 2008, there is not a benchmarking standard yet.

The aim of benchmarking measures in our methodology is to define projects' data attributes which should be collected in organizations to build an effective benchmarking data repository. In defining these attributes several points were taken into account. Firstly, these attributes were chosen based on compatibility with project attributes of ISBSG data repository. This compatibility will let organizations to follow the same standardization efforts which ISBSG tries to make. Secondly, projects attributes which includes important information for organizations were selected as benchmarking measures in this methodology. Thirdly, we examined each selected benchmarking measure to find out if they can be collected in practice in other organizations or not. Also, applicability of each of these measures was inspected in three different organizations.

In our study 49 attributes are considered for the purpose of benchmarking data collection. These attributes are classified into 6 groups of attributes which are Submission Attributes, Project Attributes, Product Attributes, Size Attributes, Effort Attributes, and Productivity Factors. Following are the definition of these groups and included attributes:

3.1.1. Submission Attributes

The information of project data submitter is collected under this group. The reason behind collecting this data is to provide information for benchmarking data repository managers to contact to the person who submitted the project data to get more detailed information in necessary situations. In order to provide confidentiality, this group of data attributes is only visible to administrators.

ID of the Attribute: A1	**Description:** Name and surname of the person who fills in the questionnaire
Name: Contact Person	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of Benchmarking data collection	**Collector:** NA

ID of the Attribute: A2	**Description:** Name of the company/organization
Name: Company	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of Benchmarking data collection	**Collector:** NA

ID of the Attribute: A3	**Description:** Phone number of the contact person
Name: Phone Number	
Scale: Nominal	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of Benchmarking data collection	**Collector:** NA

ID of the Attribute: A4	**Description:** E-mail of the contact person
Name: E-mail	
Scale: Nominal	**Measure Type:** Noun and Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of Benchmarking data collection	**Collector:** NA

ID of the Attribute: A5	**Description:** Role of the contact person in the organization. i.e. Project Manager, Team Leader, Software Engineer...
Name: Role of the Submitter	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the questionnaire	**Collector:** NA

ID of the Attribute: A6	**Description:** Date in which the questionnaire is filled in
Name: Submission Date	
Scale: Ordinal	**Measure Type:** Date
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of Benchmarking data collection	**Collector:** NA

3.1.2. Project Attributes

The information specific to a project is collected under project attributes group. Project attributes collect information such as project name, project start and end date, project type, industry type, functional domain type, development team, and other information about the project. These attributes will be used in selecting homogenous projects data for effort estimation.

ID of the Attribute: B1	**Description:** Name of the project
Name: Name of the Project	
Scale: Nominal	**Measure Type:** Date
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager

ID of the Attribute: B2	**Description:** Start date of the project in the format of DD/MM/YY. If the exact date is not known MM/YY is acceptable
Name: Project Start Date	
Scale: Ordinal	**Measure Type:** Date
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager

ID of the Attribute: B3	**Description:** End date of the project in the format of DD/MM/YY. If the exact date is not known MM/YY is acceptable
Name: Project End Date	
Scale: Ordinal	**Measure Type:** Date
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager

ID of the Attribute: B4	**Description:** Classification of the project based on whether it is New Development, Enhancement, Maintenance or Redevelopment
Name: Project Type	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager
Detailed Description: (a) New Development—At least %90 of the system is developed	

from scratch or totally new. (b) Maintenance— The system is in use, however, functions added, updated or deleted. At least % 90 of the system is protected; % 10 of the system is new developed. (c) Enhancement —Modification percentage on an existing system can be from %10 to % 90. (d) Redevelopment---- The system is rebuild based on an existing system without making any changes on functional requirements. (ref. IPA/SEC)

ID of the Attribute: B5	**Description:** Classification of the projects in one of the industry types based on the given list.
Name: Industry Type	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager
Detailed Description: (a) Information Systems and Communications, (b) Finance, (c)Transport, (d) Wholesale and Trail, (e) Manufacturing, (f)Medical, Healthcare, (g)Education and Learning, (h)Government (i) Insurance (adopted from IPA/SEC)	

ID of the Attribute: B6	**Description:** Classification of the projects in one of the industry types based on the given list.
Name: Functional Domain Type	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager
Detailed Description: Char Method ISO/IEC 14143-5	

Functional Domain Type	**Control- and Communication-Rich**	**Data-Rich**	**Manipulation- and Algorithm-Rich**
Pure Data Handling System	negligible	dominant	negligible
Information System	negligible	dominant	present
Data Processing System	negligible	present	present
Controlling Information System	present	dominant	negligible
Controlling Data System	present	present	negligible
Complex Controlling Information	present	dominant	present

System			
Non-Specific (Complex) System	present	present	present
Simple Control System	dominant	negligible	negligible
Control System	present	negligible	present
Complex Control System	dominant	negligible	present
Data Driven Control System	dominant	present	negligible
Complex Data Driven Control System	dominant	present	present
Pure Calculation System	negligible	negligible	dominant
Controlling Calculation System	present	negligible	dominant
Scientific Information System	negligible	present	dominant
Scientific Controlling Data Processing System	present	present	dominant

ID of the Attribute: B7	**Description:** It is new business if the project is new in one of the industry or functional domain types
Name: New Business Area or not	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager

ID of the Attribute: B8	**Description:** Weather new technology is used in the project or not. Architecture, platform, programming language and DBMS should be considered.
Name: New Technology or not	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the beginning of the project	**Potential Collector:** Project Manager

ID of the Attribute: B9	**Description:** What kind of tool support has been used during development process? i.e. IDE, CVS, CASE Tools
Name: Tools’ Use	
Scale: Nominal	**Measure Type:** Noun

Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: B10	**Description:** Programming and tool skills, experiences of the development team members on average in years. i.e: 2 years
Name: Experiences of the development team members	
Scale: Ratio	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: At the initiation phase of the project	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: B11	**Description:** Number of the people who involved in the one of the phases of the project.
Name: Number of the team members	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: B12	**Description:** Degree of the team member change for the whole software life cycle.
Name: Stability of the team	
Scale: Ratio	**Measure Type:** Number
Type: Derived	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader
Formula: (Number of the changed members)/Total numbers of team members	

3.1.3. Product Attributes

The information related to products is collected under this category. Product attributes include programming language, data base management system, architecture, software development methodology, information related to platform, and reuse rate. These attributes will also be used in selecting homogenous projects data for effort estimation.

ID of the Attribute: C1	**Description:** Name of the programming language used in the project
Name: Programming Language	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader
Detailed Description: (a) Assembly language, (b) COBOL, (c) PL/I, (d) C++, (e) Visual C++, (f) C, (g) VB,(h)Excel (VBA), (i)PL/SQL, (j): C#, (k) ABAP, (l): Visual Basic.NET, (m) Java, (n) Perl, (o) Shell script, (p) Delphi, (r)HTML, (s) XML. (ref. IPA/SEC)	

ID of the Attribute: C2	**Description:** Name of the data base management system used in the project
Name: DBMS	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader
Detailed Description: a: Oracle, b: SQL Server, c: PostgreSQL, d: MySQL, e: Sybase, f: Informix, g: ISAM, h: DB2, i: Access, j: HiRDB, k: IMS, l: Other (description), m: None. (ref. IPA/SEC)	

ID of the Attribute: C3	**Description:** Name of the architecture type used in the developed project.
Name: Architecture	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader
Detailed Description: a: Stand-alone b: Client/Server Model (2 tier, 3 tier...) c: Search Oriented Architecture d: Service Oriented Architecture e: Distributed Computing f:Peer to Peer g: Other	

ID of the Attribute: C4	**Description:** Name of the life cycle model followed in the project. i.e. Waterfall, Iterative, Evolutionary, Spiral, Agile, Object Oriented other.
Name: Software Development Methodology	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: C5	**Description:** Does the organization has CMM, CMMI, SPICE certification or not.
Name: Process improvement standard existence	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: C6	**Description:** If the project is conducted based on standards or not. IEEE-830-1998, IEEE-1058-1998,etc.
Name: Standard Use	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: C7	**Description:** What is the target operating system? i.e. Linux, Unix, .Net, Java
Name: Platform Use	
Scale: Nominal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After the project planning phase	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: C8	**Description:** What is the Algorithm complexity level which is used in project?
Name: Algorithm Complexity Level	
Scale: Ordinal	**Measure Type:** Noun
Type: Base	**Collection Frequency:** Once
Collection Time: After requirements and design phase	**Potential Collector:** Project Manager, Team Leader
Detailed Description: These three levels of complexity is interpretation of algorithm complexity in subjective way. 1. Basic Algorithms (Level 1): Small algorithms include only basic mathematical calculations and simple data manipulations which are: Derived data creation by transforming existing data, Mathematical formulas/calculations, Condition analysis to determine which are applicable, Data validation, Equivalent-value conversion, and Data filtering/selection by specified criteria. This classification of data manipulation is adopted from action type list defined in Santillo & Abran (2006). 2. Medium complex algorithms (Level 2): Algorithms in this level include medium complex algorithms which have different operations than defined action type above (defined in the basic algorithms), and in these algorithms there isn't any integration with other algorithms in the system. Also, in this kind of algorithms there isn't parallel and multitasking usage of processes. In this level the input of algorithms are a group of parameters, and the result of medium complexity operation can be one or several outputs. 3. Very complex algorithms (Level 3): Algorithms which includes very complex operations, and there is integration with other algorithms. In this kind of algorithms extra hardware are involved. In addition, in this kind of algorithms, there are real time criteria as limitation factors.	

ID of the Attribute: C9	**Description:** Percentage of reused LOC of software components.
Name: Reuse rate of source code	
Scale: Ratio	**Measure Type:** Number
Type: Derived	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader
Formula: %software component reused By reuse we mean the percentage of effort consumed for reusing.	

3.1.4. Size Attributes

The size of software projects are measured by using the COSMIC function size measurement according to ISO/IEC as an international standard. Project size data is collected in BFC level, and not only numerical information is kept, but also functional requirements, data groups, object of interests, and data movements are collected under this attribute group. In this case it is possible to calculate functional similarity which reflects the project size better.

ID of the Attribute: D1	**Description:** Detailed size data in COSMIC (functional requirements, data groups, object of interest, and data movements)
Name: Detailed Size Data in COSMIC	
Scale: ratio	**Measure Type:** number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer
Detailed Description: Project size is measured by using COSMIC method, and detailed size data of the project is collected.	

ID of the Attribute: D2	**Description:** Number of Entries in COSMIC measurement
Name: Number of Entries	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer

ID of the Attribute: D3	**Description:** Number of Exits in COSMIC measurement
Name: Number of Exits	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer

ID of the Attribute: D4	**Description:** Number of Reads in COSMIC measurement
Name: Number of Reads	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer

ID of the Attribute: D5	**Description:** Number of Writes in COSMIC measurement
Name: Number of Writes	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer

ID of the Attribute: D6	**Description:** Number of Functional Processes in COSMIC measurement
Name: Number of Functional Processes	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: In the project planning phase	**Potential Collector:** Project Manager, software engineer
Detailed Description: Number of identified functional processes in COSMIC functional size measurement of the project.	

ID of the Attribute: D7	**Description:** Number of Added functionality in COSMIC measurement
Name: Added functionality	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:**
Collection Time: During project	**Potential Collector:** Project Manager, software engineer
Detailed Description: Number of added functionality in COSMIC functional size measurement of the project. The baseline for added functionality is the original version of the project which the COSMIC functional size measure is calculated.	

ID of the Attribute: D8	**Description:** Number of Deleted functionality in COSMIC measurement
Name: Deleted functionality	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:**
Collection Time: During project	**Potential Collector:** Project Manager, software engineer
Detailed Description: Number of Deleted functionality in COSMIC functional size measurement of the project. The baseline for deleted functionality is the original version of the project which the COSMIC functional size measure is calculated.	

ID of the Attribute: D9	**Description:** Number of Changed functionality in COSMIC measurement
Name: Changed functionality	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:**
Collection Time: During project	**Potential Collector:** Project Manager, software engineer
Detailed Description: Number of Changed functionality in COSMIC functional size measurement of the project. The baseline for changed functionality is the original version of the project which the COSMIC functional size measure is calculated.	

ID of the Attribute: D10	**Description:** Reflective functional similarity size
Name: Reflective functional similarity size	
Scale: ratio	**Measure Type:** number
Type: derived	**Collection Frequency:** Once
Collection Time: In the project planning phase, after completion of measurement	**Potential Collector:** Project Manager, software engineer
Detailed Description: Project size is measured by using COSMIC method, and reflective functional similarity is calculated using detailed size of project (OzanTop O., 2008)	

3.1.5. Effort Attributes

Effort data is collected based on ISO 12207 Software life cycle processes standard under 11 categories: Project management activities, requirements definition activities, design activities, coding activities, software integration activities, Testing activities, system installation activities, operation activities, quality assurance activities, quality management activities, and maintenance activities. As mentioned before, these effort attributes are defined based on ISO 12207 standard, and in this international standard the use of any particular life cycle model is not required. So, by following various types of life cycle models such as waterfall, incremental development, evolutionary development, and etc. it is possible to detect defined efforts. Thus, categorization of effort data is life cycle independence. Moreover, Effort data for each of these activities are kept in detailed level. Based on the level of effort data and how these data is collected, quality of effort data is classified into three levels.

ID of the Attribute: E1	**Description:** Total actual effort in person hours for the whole project life cycle.
Name: Actual Total Effort in person hours	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader

ID of the Attribute: E2.1	**Description:** Total actual effort in person hours for the project management activities. For details check detailed description.
Name: Total Actual Effort Project Management Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: During the project life cycle	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Project Management Activities include: **6.3.1 Project Planning Activities:** to determine the scope of the project management and technical activities, process outputs, project tasks and deliverables; to establish schedule for project task conduct, including achievement criteria, and required resources to accomplish project tasks. **6.3.2 Project Assessment and Control Activities**: to determine the status of the project and ensure that the project performs according to plans and schedules, and within projected budgets, and that it satisfies technical objectives.	

6.3.3 Decision Management Activities: to select the most beneficial course of project action where alternatives exist. **6.3.4 Risk Management Activities**: to identify, analyze, treat and monitor the risks continuously. **6.3.5 Configuration Management Activities**: to establish and maintain the integrity of all identified outputs of a project or process and make them available to concerned parties. **6.3.6 Information Management Activities**: to provide relevant, timely, complete, valid and, if required, confidential information to designated parties during and, as appropriate, after the system life cycle **6.3.7 Measurement Activities**: to collect, analyze, and report data relating to the products developed and processes implemented within the organizational unit, to support effective management of the processes, and to objectively demonstrate the quality of the products.

ID of the Attribute: E2.2	**Description:** Total actual effort in person hours for the requirements definition activities. For details check detailed description.
Name: Total Actual Effort Requirements Definition Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the requirement definition activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Requirements Definition Activities include: **6.4.1 Stakeholder Requirements Definition Activities:** The purpose of the Stakeholder Requirements Definition Process is to define the requirements for a system that can provide the services needed by users and other stakeholders in a defined environment. It identifies stakeholders, or stakeholder classes, involved with the system throughout its life cycle, and their needs and desires. It analyzes and transforms these into a common set of stakeholder requirements that express the intended interaction the system will have with its operational environment and that are the reference against which each resulting operational service is validated in order to confirm that the system fulfills needs. **6.4.2 System Requirements Analysis Activities:** The purpose of System Requirements Analysis is to transform the defined stakeholder requirements into a set of desired system technical requirements that will guide the design of the system. **7.1.2 Software Requirements Analysis Activities:** The purpose of Software Requirements Analysis Process is to establish the requirements of the software elements of the system.	

ID of the Attribute: **E2.3**	**Description:** Total actual effort in person hours for the design activities. For details check detailed description.
Name: Total Actual Effort Design Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the design activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Design Activities include: **6.4.3 System Architectural Design Process**: The purpose of the System Architectural Design Process is to identify which system requirements should be allocated to which elements of the system. **7.1.3 Software Architectural Design Activities:** The purpose of the Software Architectural Design Process is to provide a design for the software that implements and can be verified against the requirements **7.1.4 Software Detailed Design Process:** The purpose of the Software Detailed Design Process is to provide a design for the software that implements and can be verified against the requirements and the software architecture and is sufficiently detailed to permit coding and testing.	

ID of the Attribute: **E2.4**	**Description:** Total actual effort in person hours for the software coding activities. For details check detailed description.
Name: Total Actual Effort Software Coding Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the coding activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: **7.1.5 Software Construction Activities:** This process includes the activities to produce executable software units that properly reflect the software design.	

ID of the Attribute: E2.5	**Description:** Total actual effort in person hours for the software integration activities. For details check detailed description.
Name: Total Actual Effort Software Integration Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the Software Integration Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Software Integration Activities include; **6.4.5 System Integration Process:** The purpose of the System Integration Process is to integrate the system elements (including software items, hardware items, manual operations, and other systems, as necessary) to produce a complete system that will satisfy the system design and the customers' expectations expressed in the system requirements. **7.1.6 Software Integration Activities:** This process is to combine the software units and software components, produce integrated software items.	

ID of the Attribute: E2.6	**Description:** Total actual effort in person hours for the software testing activities. For details check detailed description.
Name: Total Actual Effort Testing Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the Software Testing Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Testing Activities include; **6.4.6 System Qualification Testing Activities**: Systems Qualification Testing Process includes the activities to ensure that the implementation of each system requirement is tested for compliance and that the system is ready for delivery. **7.1.7 Software Qualification Testing Activities:** This process includes the activities to confirm that the integrated software product meets its defined requirements.	

ID of the Attribute: E2.7	**Description:** Total actual effort in person hours for the system installation activities. For details check detailed description.
Name: Total Actual Effort System Installation Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once

Collection Time: At the end of the Software Installation and Acceptance Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: System Installation Activities include; **6.4.7 System Installation Activities**: The purpose of the Software Installation Process is to install the software product that meets the agreed requirements in the target environment.	

ID of the Attribute: E2.8	**Description:** Total actual effort in person hours for the operation activities. For details check detailed description.
Name: Total Actual Effort Operation Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the Operation Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: This process includes the activities to operate the software product in its intended environment and to provide support to the customers of the software product.	

ID of the Attribute: E2.9	**Description:** Total actual effort in person hours for the software quality assurance activities. For details check detailed description.
Name: Total Actual Effort Software Quality Assurance Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the Software Quality Assurance Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Software Quality Assurance Activities Include; **7.2.3 Software Quality Assurance Process:** The purpose of the Software Quality Assurance Process is to provide assurance that work products and processes comply with predefined provisions and plans. **7.2.4 Software Verification Process:** The purpose of the Software Verification Process is to confirm that each software work product and/or service of a process or project properly reflects the specified requirements. **7.2.5 Software Validation Process:** The purpose of the Software Validation Process is to confirm that the requirements for a specific intended use of the software work product are	

fulfilled. **7.2.6 Software Review Process:** The purpose of the Software Review Process is to maintain a common understanding with the stakeholders of the progress against the objectives of the agreement and what should be done to help ensure development of a product that satisfies the stakeholders. Software reviews are at both project management and technical levels and are held throughout the life of the project. **7.2.7 Software Audit Process:** The purpose of the Software Audit Process is to independently determine compliance of selected products and processes with the requirements, plans and agreement, as appropriate

ID of the Attribute: E2.10	**Description:** Total actual effort in person hours for the quality management activities. For details check detailed description.
Name: Total Actual Effort Quality Management Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the Quality Management Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: This process includes the activities to assure that products, services and implementations of life cycle processes meet organizational quality objectives and achieve customer satisfaction	

ID of the Attribute: E2.11	**Description:** Total actual effort in person hours for the maintenance activities. For details check detailed description.
Name: Total Effort for Maintenance Activities	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the Maintenance Activities	**Potential Collector:** Project Manager, Team Leader
Detailed Description: **6.4.10 Software Maintenance Process**: The purpose of the Software Maintenance Process is to provide cost-effective support to a delivered software product.	

ID of the Attribute: E3	**Description:** This question addresses how the actual effort data was collected in the organization. Potential answers are –using timesheets in daily bases, weekly bases, or at the end of the month; using MS project...
Name: What kinds of procedures were used for the record of the effort?	
Scale: Nominal	**Measure Type:** Noun Phrase
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader

3.1.6. Productivity Factors

Productivity factors which have influence on productivity and effort of the project are collected under this attribute group. These productivity factors are: reliability, usability, maintainability, efficiency, and portability. Data related to these factors are gathered in ordinal scale from a level of 1 to 5.

ID of the Attribute: F1	**Description:** Requirement volatility is a measure of how much software requirements change (added, deleted and modified) after agreed on a set of requirements by both client and supplier.
Name: Requirements volatility	
Scale: Ratio	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader
Detailed Description: **Requirements Volatility Percentage= (added+ deleted+ modified requirements)/(total Number of requirements in the specific version)**	

ID of the Attribute: F1	**Description:** Does a standard or body impose nonfunctional requirements in software.
Name: Nonfunctional requirements	
Scale: Ordinal	**Measure Type:** Number
Type: Base	**Collection Frequency:** Once

Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader
Detailed Description: Nonfunctional requirements: **Reliability:** Ability of software to behave consistently in an acceptable manner Give a range from 1 to 5 based on the intensity reliability intensity imposed in the project. 1 is the lowest, 5 is the highest reliability **Usability:** Usability of user interface. Give a range from 1 to 5 based on the intensity of the usability requirements in the project. 1 is the lowest, 5 is the highest usability **Maintainability** Level of cohesion and coupling. Give a range from 1 to 5 based on the intensity maintainability requirements in the project. 1 is the lowest, 5 is the highest maintainability **Efficiency:** The level at which software uses system resources. Give a range from 1 to 5 based on the intensity efficiency requirements in the project. 1 is the lowest, 5 is the highest efficiency **Portability:** The degree of ease to port software running on one system environment to another one. Give a range from 1 to 5 based on the intensity portability requirements in the project. 1 is the lowest, 5 is the highest portability.	

ID of the Attribute: **F3**	**Description** Is the system Safety Critical or not. What is the level of it?
Name: Is the system Safety Critical or not. What is the level	
Scale: Nominal	**Measure Type:** Number
Type: Base	**Collection frequency:** Once
Collection Time: At the end of the project	**Potential Collector:** Project Manager, Team Leader

3.2. Benchmarking Data Collection Processes

For the purpose of constructing a reliable benchmarking data repository, not only projects measures are important, but also data collection processes play critical role in improving quality of benchmarking projects data (Ozantop, Nabi, & Demirors, 2011). So, in order to improve the accuracy and consistency of the benchmarking data, data collection processes are defined and modeled based on software development stages in our methodology. These processes are based on Ozcan Top and Demirors (2011) technical report and refined in this section. In these data collection processes it is determined that in which stage of software development, which data, and from where should be collected. The benchmarking data collection processes are modeled in ARIS modeling tool by utilizing the Event-driven process chain (EPC) notations. In the first level of these processes, data collection infrastructure and Cubit infrastructure is defined, then in the next stage data collection process begins, and projects data are collected in the subsequent stages of the processes. These processes and sub processes are:

1. Infrastructure Definition Process
2. Cubit Infrastructure Definition Process
3. Data Collection Process
    - 3.1. Submission Attributes Data Collection Process
    - 3.2. Project Attributes Data Collection Process
    - 3.3. Product Attributes Data Collection Process
    - 3.4. Software Attributes Data Collection Process size
        - 3.4.1. Measure COSMIC size
4. Effort Attributes Data Collection Process
    - 4.1. Data Collection Process for Project Management Effort Data
    - 4.2. Data Collection Process for Requirements' Activities Effort Data
    - 4.3. Data Collection Process for Design Activities' Effort Data
    - 4.4. Data Collection Process for Integration Activities' Effort Data
    - 4.5. Data Collection Process for Test Activities' Effort Data
    - 4.6. Data Collection Process for Quality Activities' Effort Data

EPC is a dynamic modeling notation to present flow of activities in processes by unifying static resources of business such as systems, organizations, data, etc. (Davis & Brabander 2007)

There are four basic type of objects used in EPC: Events, Functions, Rules, and Resources like data, systems, organizations, etc. Events represent the external changes which trigger the start of the process, internal changes of states by preceding the process, and the final outcome of the process. They present the pre-conditions and post-conditions for each step of processes. Functions represent the activities and tasks which are executed as part of processes and they receive inputs, creates outputs, and use resources. An event can trigger a function, and a function creates one or more events (Davis & Brabander 2007).

To illustrate the flow of process models, combination of rules with functions and events are used. There are three types of rules: OR, XOR, and AND rules (Davis & Brabander 2007). The object symbol and their descriptions which are used in the benchmarking collection processes are given in Table 1.

Table 1: EPC model objects used in benchmarking data collection processes (Davis & Brabander 2007)

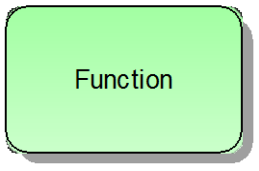
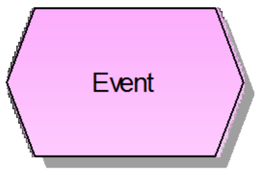
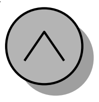
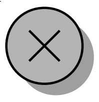
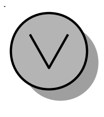
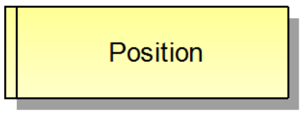
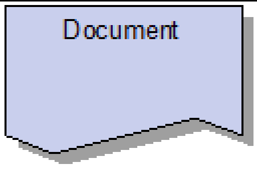
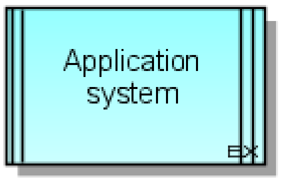
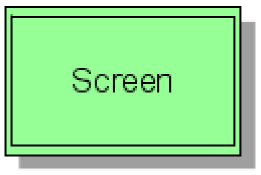
Object Name	Object Symbol	Object Description
Function		A function represents the activities and tasks.
Event		An event represents the external changes which trigger the start of the process, internal changes of states by preceding the process, and the final outcome of the process.
AND		Following a function, process flow splits into two or more parallel paths. Preceding a function, all events must occur in order to trigger the following function.
XOR		Following a function, one, but only one, of the possible paths will be followed. Preceding a function, one, but only one, of the possible events will be the trigger.

Table 1: EPC model objects used in benchmarking data collection processes (Davis & Brabander 2007) (Continued)

Object Name	Object Symbol	Object Description
OR		Following a function, one or many possible paths will be followed as a result of the decision. Preceding a function, any one event, or combination of events, will trigger the function.
Position		A position is Role performed by individual person.
Document		Document is an Information Carrier.
Application System		A software system running on a computer used to support the carrying out of a function.
Screen		The design of a particular display screen format (GUI) used by a system to support functions requiring user input or displaying information to users.

3.2.1. Infrastructure Definition Process

Defining infrastructure is the first process in benchmarking data collection. In this process project manager, quality manager, software engineer, or benchmarking data manager is responsible for theoretical defining infrastructure for the organization. This process begins by a motivation for data collection and the purpose of the benchmarking data collection is identified in the first place. Subsequently, attributes of data collection is identified and each attribute will be defined. In this stage the reports and tools which will be used in data collection process, the frequency of data collection, and also responsible people for data collection are identified.

3.2.2. Cubit Infrastructure Definition Process

Benchmarking data collection Cubit infrastructure is defined in this process. Benchmark data manager defines Cubit infrastructure for a specific project. As a first step, an account (user and password) is requested from Cubit manager for benchmark data manager of the organization. After receiving Cubit account information, benchmark data manager logs in to Cubit and defines users for benchmark responsible persons in the organization, and send user information to responsible persons. In order to collect benchmarking data, benchmarking questions, answer types, and questions types are defined by benchmarking data manager as a Cubit benchmarking infrastructure for target organization.

3.2.3. Data Collection Process

In this process, benchmarking data manager or benchmarking responsible person define the project. Subsequently data related to projects attributes, product attributes, software size measurement, project efforts, and productivity factors data are collected. This process contains sub processes for collecting each benchmarking attributes category.

3.2.3.1. Project Data Collection Process

In this process project attributes such as project name, project start and end date, project type, industry type, functional domain type, development team, and other information about the project are collected. Project attributes data are extracted by data submitter from related reports or documents. First, project Charter is checked for identifying project name, and project name is entered using answer benchmarking questions screen of Cubit. The next steps are to check out project plan, Gantt chart, and Work Breakdown Structure (WBS) to identify project start and end date, and then submitting them to Cubit. In order to find project type and industry type of the target project Software Requirement Specification (SRS) and attribute definition document (or organization benchmark report) should be examined. Project management plan and human resource management record are other artifacts which should be examined to extracting project attributes data.

3.2.3.2. Product Data Collection Process

Benchmarking data for product attributes category are collected in this process. Product data should be extracted from relevant documents and reports, and then submitted to the Cubit by using benchmarking screens. In order to identify programming language attribute, submitter should refer to SRS, technical management plan, and also attribute definition document. Software design and architecture design are the next documents which should be checked for identifying architecture type of the project. Following these, software development methodology is identified by referring to project management plan and also attribute definition document. Technical management plan and source code are other items which should be used for identifying other product attributes in an organization.

3.2.3.3. Software Size Data Collection Process

Software size attributes data are collected in this process. As a first step, size measurement tool should be identified, and then software size of the target project is measured by using COSMIC measurement method. The number of Entries, Exits, Reads, and Writes in COSMIC measurement of the project are counted, then total size in COSMIC Function Point (CFP) is calculated. The number of functional processes, new added functionalities, deleted functionalities, and modified functionalities are identified and submitted to the CUBIT.

3.2.3.3.1. Software Functional Size Measurement Process

In this sub process, the process of functional size measurement of the project is defined. First, measurement scope should be identified by referring to SRS, user manuals, and user screens of the software. The boundaries should be identified in the next step. Functional processes, object of interests, data groups, data movements, added functionalities, deleted functionalities, and changed functionalities are identified by using COSMIC measurement method. Finally, total size in CFP is calculated, and size measurement is verified by Cubit.

3.2.4. Effort Data Collection Process

Data Collection process for effort attributes are given in this process. In this process effort for each effort attributes, which were identified in benchmarking measures section (section 3.1) are collected (see APPENDIX). The first step is to identify effort for project management activities which is done in “Data Collection Process for Project Management Effort Data” sub process. The next step is to identify effort for requirement definition activities; this step is also elaborated in “Data Collection Process for Requirements’ Activities Effort Data” sub process in section 3.2.4.2. Following, effort of design activities is collected in “Data Collection Process for Design Activities’ Effort Data” sub process. As the next task, in order to identify effort for coding activities, work items related with coding activities are determined by referring to project plan, WBS, WBS Dictionary, and project schedule. Then effort records are mapped to work items of coding activities. Subsequently, effort for Integration activities, and testing activities are identified by following “Data Collection Process for Integration Activities’ Effort Data”, and “Data Collection Process for Test Activities’ Effort Data” sub processes respectively. The next steps are identifying items related to installation activities, and operation activities to find effort of each of these activities. These items should be extracted from project plan, WBS, WBS Dictionary, and project schedule. After mapping and summing effort records to work items, work effort for both installation, and operation activities are collected. Next, effort for software quality assurance activities are collected by following “Data Collection Process for Quality Activities’ Effort Data” sub process. The next tasks are identifying effort for quality management and maintenance activities similar to the tasks done for identifying effort of coding activities. As a last task in this process, the procedures which were used for the record of effort are identified.

3.2.4.1. Data Collection Process for Project Management Effort Data

In this Sub process, data collection process of effort data for project management activities is elaborated. First step is to identify work items related to developing Project Plan (6.3.1) by referring to Project Plan, WBS, WBS Dictionary, and project schedule. Then, effort records are extracted from timesheet application (or any other effort record), and these records are mapped to identified work items, and the total effort for project planning activities are calculated and submitted to Cubit. The next tasks are identifying work items related with project assessment and control activities (6.3.2), decision management activities (6.3.3), Risk management activities (6.3.4), configuration management activities (6.3.5), information management activities (6.3.6), and measurement activities (6.3.7) respectively in order to find effort consumed for these activities. For all these tasks the same procedure which was done for developing project plan will be pursued. At the end, total effort for project management activities will be calculated and submitted to Cubit.

3.2.4.2. Data Collection Process for Requirements Activities' Effort Data

Effort data for requirement activities are collected in this sub process. In this process effort data for stakeholder requirement definition activities (6.4.1), system requirement analysis activities (6.4.2), and software requirement analysis activities (7.1.2) are collected. For this purpose, first work items related with each of these activities are identified by referring to Project Plan, WBS, WBS Dictionary, and project schedule. Then effort records are mapped to these work items and total effort for each of these activities are found and submitted to Cubit. After finding effort data for all of these activities the total effort for requirement phase is calculated and also submitted.

3.2.4.3. Data Collection Process for Design Activities' Effort Data

In this sub process, effort data for design activities are collected. In order to find effort consumed for each design activity of system architectural design activities (6.4.3), software architectural design activities (7.1.3), and software detailed design activities (7.1.4), related work items should be identified. Then effort records which are extracted from timesheet or other artifact are mapped to these work items. After mapping effort record to work items, the sums of effort of each activity are submitted to cubit. Lastly, total effort for all activities is calculated as effort of design phase.

3.2.4.4. Data Collection Process for Integration Activities' Effort Data

Effort data for Integration activities are collected in this sub process. In this process effort data for System Integration activities (6.4.5) and Software Integration activities

(7.1.6) are collected. For this purpose, first work items related with each of these activities are identified by referring to Project Plan, WBS, WBS Dictionary, and project schedule. Then effort records are mapped to these work items and total effort for each of these activities are found and submitted to Cubit. After finding effort data for all of these activities the total effort for Integration phase is calculated and also submitted to Cubit.

3.2.4.5. Data Collection Process for Test Activities' Effort Data

Effort data for Test activities are collected in this sub process. In this process effort data for System Qualification testing activities (6.4.6) and Software Qualification Testing activities (7.1.7) are collected. For this purpose, first work items related with each of these activities are identified by referring to Project Plan, WBS, WBS Dictionary, project schedule, Test Plan, and Test Cases. Then effort records are mapped to these work items and total effort for each of these activities are found and submitted to Cubit. After mapping effort record to work items, the sums of effort of each activity are submitted to cubit. Lastly, total effort for all activities is calculated as effort of testing phase.

3.2.4.6. Data Collection Process for Quality Activities' Effort Data

Data collection process for Quality activities' effort data is elaborated in this sub process. The first task in this process is to identify work items related with Software Quality Assurance activities (7.2.3) by referring to Quality Management Plan, Project Plan, WBS, WBS Dictionary, and project schedule. Then in order to find total effort of software quality assurance activities effort records which are extracted from timesheets are mapped to these identified work items. The next step is to identify effort data of Software Verification activities (7.2.4) by identifying related work items. These work items are extracted from Project Plan, WBS, WBS Dictionary, and project schedule artifacts. Once more effort records are mapped to these work items to determine the amount of effort consumed for software verification activities. The same procedure is followed for identifying effort data for Software Validation Activities (7.2.5). As the next task, work items related with Software Review activities (7.2.6) is identified by referring to Project Plan, WBS,

WBS Dictionary, project schedule, and Review Schedules. Afterward, total effort for software review activities are determined by mapping effort record to these identified work items. Next, effort data for Software Audit activities (7.2.7) are identified similarly by referring to Project Plan, WBS, WBS Dictionary, and project schedule artifacts. After finding effort data for all of these activities the total effort for Quality activities is calculated and also submitted to Cubit.

3.3. Benchmarking Tool

Considering benchmarking defined measures and data collection processes, an automated benchmarking data collection tool was integrated on Cubit (http://smrg.ii.metu.edu.tr/cubit/). The Cubit toolset is a web based application which have Java technologies and Groovy as an upper level language for its infrastructure. Cubit toolset is developed by using Grails framework and as DBMS the PostgreSQL rational database is used. For development of Cubit an iterative and incremental methodology was pursued. Cubit enables user to measure software projects, and collect projects size measurements details, define infrastructure for data collection, and collect benchmarking data in a reliable way.

System administrator of the Cubit is responsible to define an organization and an administrator user for the organization. Subsequently, organizational administrator can define several users within the organization.

Several projects can be defined within an organization, and then size measurement data and benchmarking data of these projects can be collected.

Use case model diagram for Cubit benchmarking is given in Figure 1.

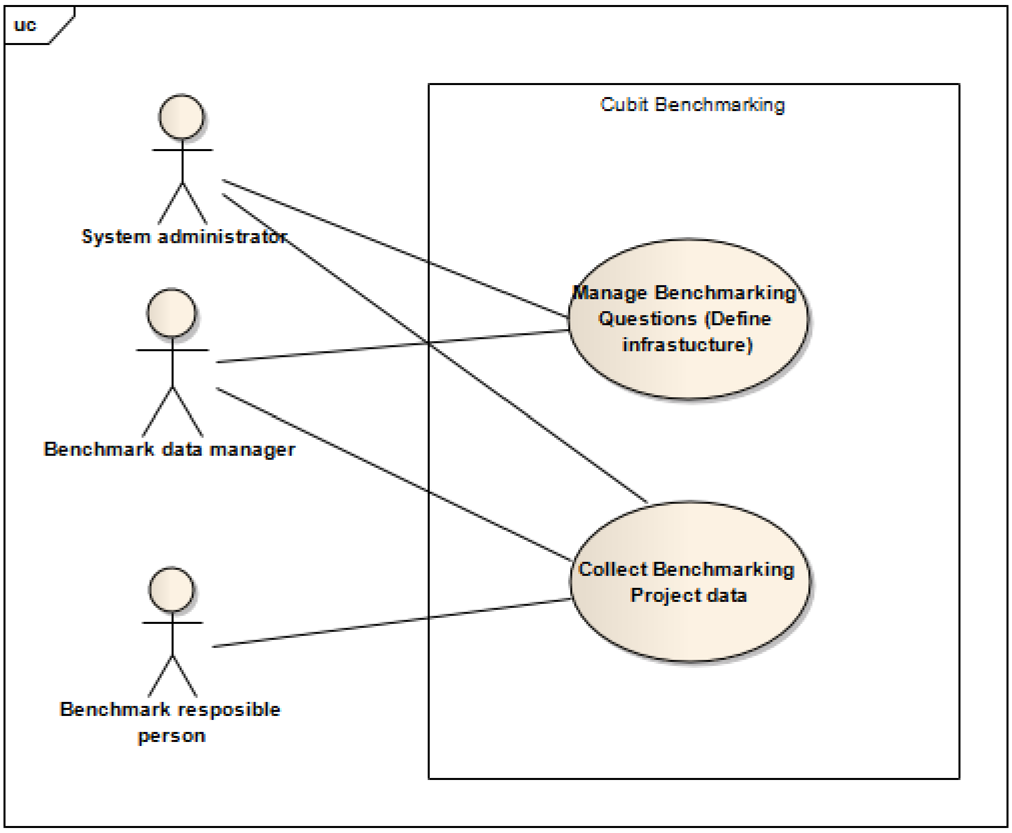
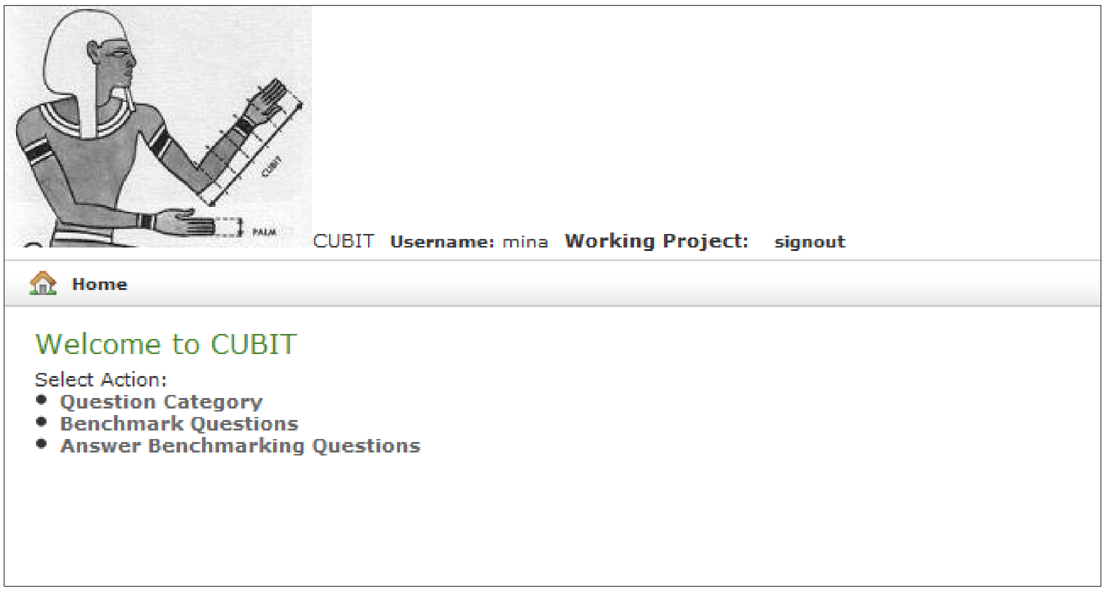

uc
Cubit Benchmarking
System administrator
Benchmark data manager
Benchmark resposible person
Manage Benchmarking Questions (Define infrastucture)
Collect Benchmarking Project data

Figure 1: Use case model for cubit benchmarking part

In the Cubit benchmarking part there are three kinds of user; system administrator, benchmarking data manager (Benchmarking administrator), and benchmarking responsible person. As mentioned before, benchmarking administrator is defined by cubit administrators for an organization. Subsequently, benchmark data administrator has the responsibility of defining users for persons who are responsible of benchmarking in the organization.

There are two use cases defined in benchmarking part; Manage benchmarking question (define cubit infrastructure), and collect benchmarking project data.



Welcome to CUBIT

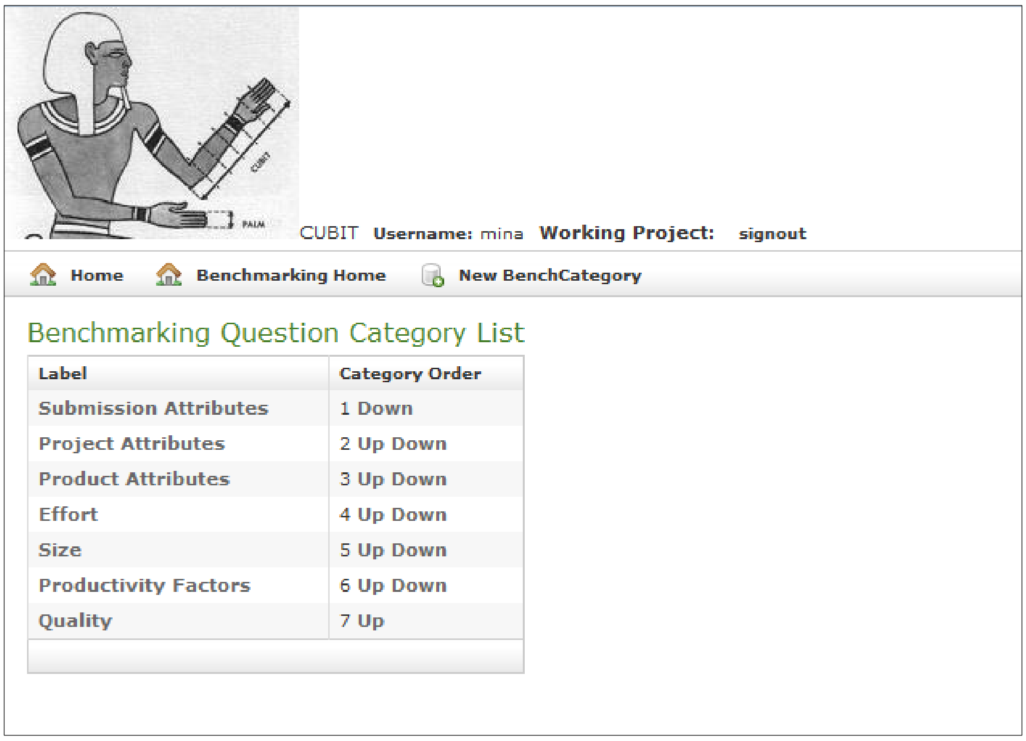
Select Action:

- Question Category
- Benchmark Questions
- Answer Benchmarking Questions

Figure 2: Benchmarking Home

In manage benchmarking question use case, users define new Question Category, modify and delete existing ones. Also, new benchmarking question can be defined, modified, deleted, and ordered. It should be mentioned that, based on our methodology there are questions defined by system administrator, but benchmarking data manager can also add new questions to question lists. In collect benchmarking project use case, user answers benchmarking questions and modify previous answers.

The screenshot of benchmarking home page is shown in Figure 2.

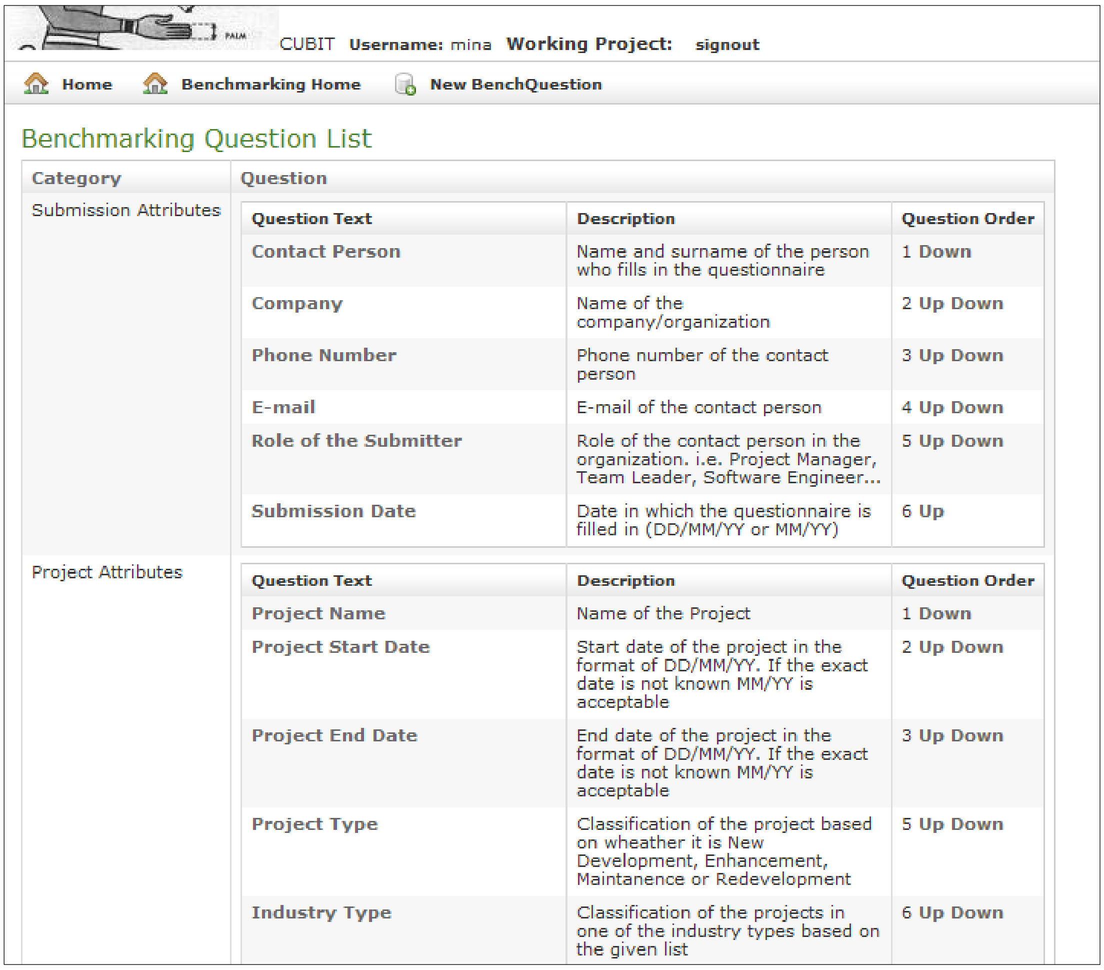


Benchmarking Question Category List

Label	Category Order
Submission Attributes	1 Down
Project Attributes	2 Up Down
Product Attributes	3 Up Down
Effort	4 Up Down
Size	5 Up Down
Productivity Factors	6 Up Down
Quality	7 Up

Figure 3: Benchmarking Question Category

To define the infrastructure of benchmarking questions, the benchmarking data administrator defines benchmarking question categories, and subsequently benchmarking questions. Figure 3 and Figure 4 depict benchmarking question category and benchmarking question lists Graphical User Interface (GUI).



CUBIT **Username:** mina **Working Project:** **signout**

Home **Benchmarking Home** **New BenchQuestion**

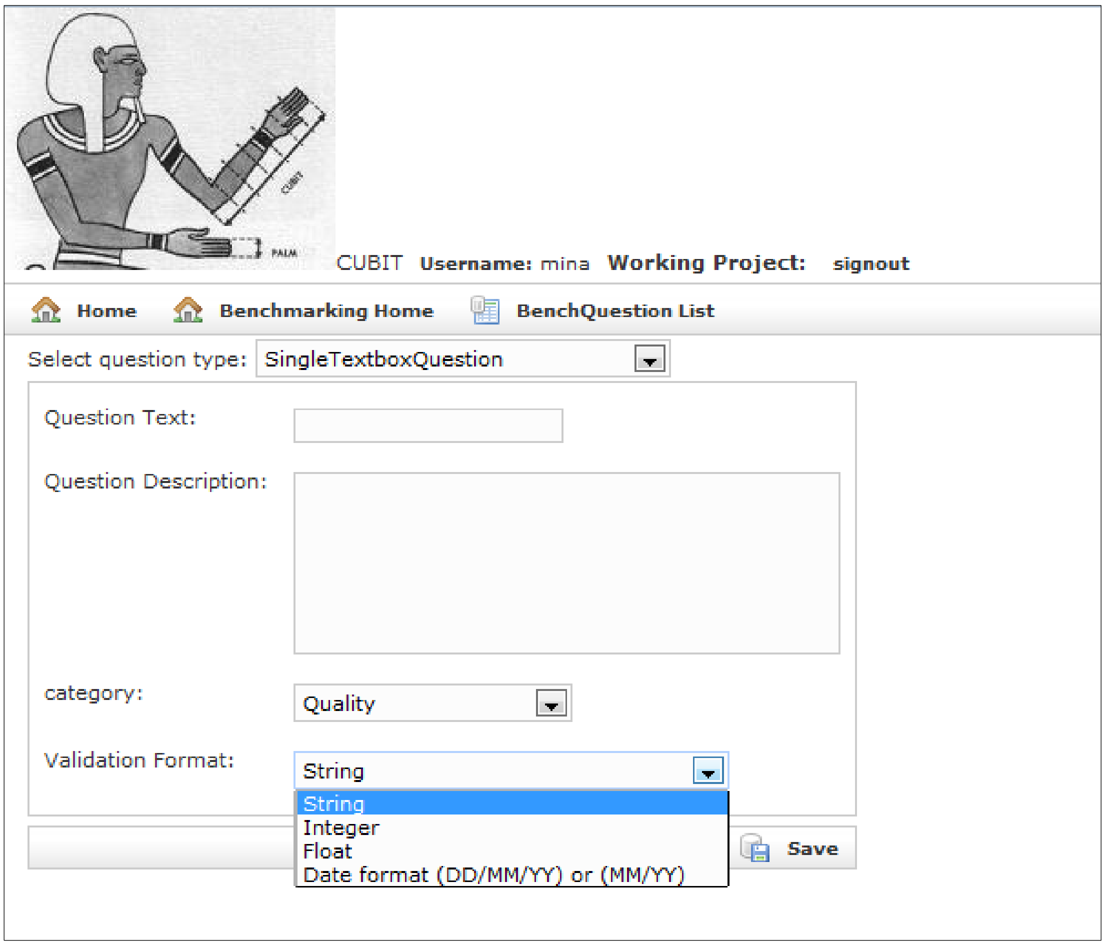
Benchmarking Question List

Category	Question Text	Description	Question Order
Submission Attributes	Contact Person	Name and surname of the person who fills in the questionnaire	1 Down
	Company	Name of the company/organization	2 Up Down
	Phone Number	Phone number of the contact person	3 Up Down
	E-mail	E-mail of the contact person	4 Up Down
	Role of the Submitter	Role of the contact person in the organization. i.e. Project Manager, Team Leader, Software Engineer...	5 Up Down
	Submission Date	Date in which the questionnaire is filled in (DD/MM/YY or MM/YY)	6 Up
Project Attributes	Project Name	Name of the Project	1 Down
	Project Start Date	Start date of the project in the format of DD/MM/YY. If the exact date is not known MM/YY is acceptable	2 Up Down
	Project End Date	End date of the project in the format of DD/MM/YY. If the exact date is not known MM/YY is acceptable	3 Up Down
	Project Type	Classification of the project based on wheather it is New Development, Enhancement, Maintanence or Redevelopment	5 Up Down
	Industry Type	Classification of the projects in one of the industry types based on the given list	6 Up Down

Figure 4: Benchmarking Question List

In order to define different questions, question types and choice types are used. There are four different question types: multiple choice questions with single answer, multiple choice questions with multiple answers, single textbox question, and multiple textbox questions. Choice type is the type of the answer a benchmark question can have, and it assesses defining different question types. It consists of: Text, checked Text, and selection choice types. Text choice type is used for the answers which has only text answer. Checked text choice type is used for the answers which enable selection and text answer. Selection type is used for multiple choice questions which the answer should be selected. In addition, validation formats (String, Date Format DD/MM/YY or MM/YY, Integer, and Float) are defined for each question and are used for validating the answer of each question. Also, a range for string, integer and float were defined to collect valid data.

Figure 5 presents the "define single textbox question" GUI. This question type is designed for benchmarking measures which has only one textual answer. As an example, this question type can be utilized in collecting "Project Name" data in project attributes category.


CUBIT Username: mina Working Project: signout

Home | Benchmarking Home | BenchQuestion List

Select question type: SingleTextboxQuestion

Question Text:

Question Description:

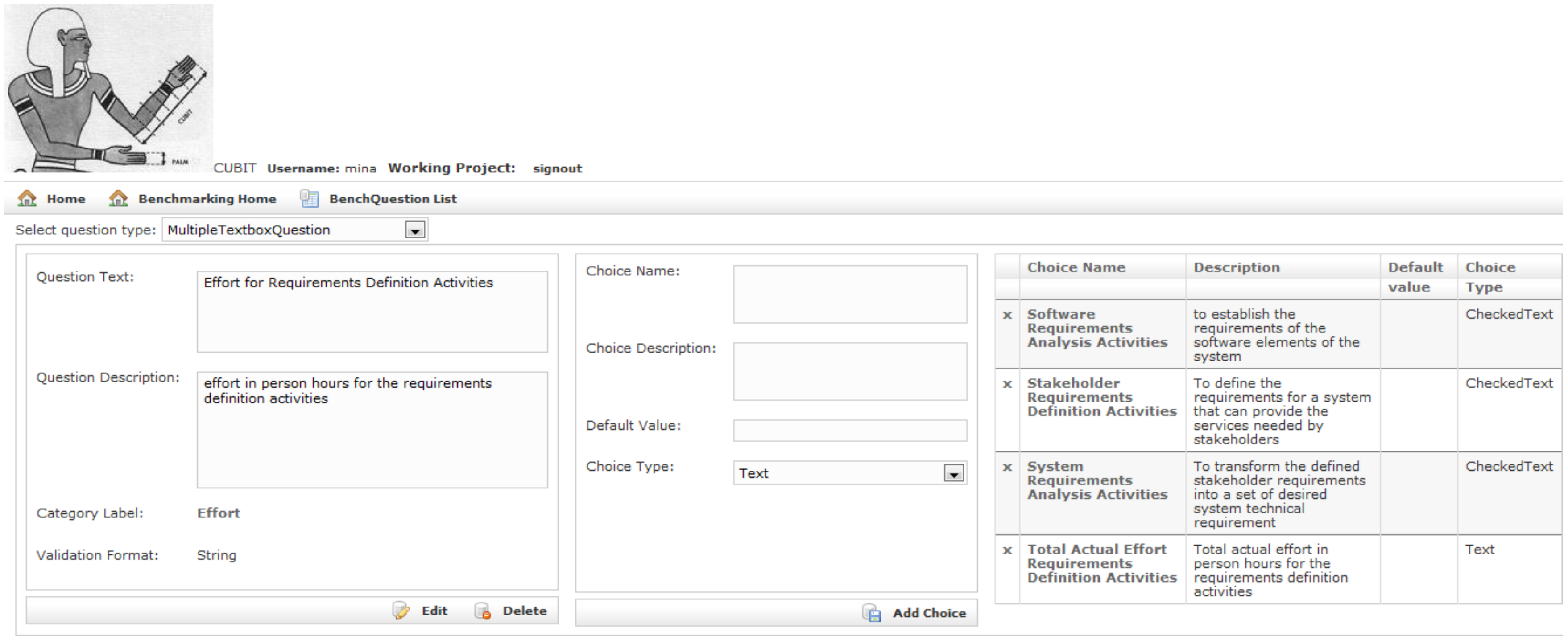
category: Quality

Validation Format: String

String
Integer
Float
Date format (DD/MM/YY) or (MM/YY)

Figure 5 Define Single Textbox Question

Figure 6 presents the "define multiple textbox question" GUI. This question type is designed for benchmarking measures which has multiple textual answers. As an example, this question type can be defined for collecting benchmarking measures of effort attributes.


CUBIT **Username:** mina **Working Project:** **signout**

Select question type: MultipleTextboxQuestion

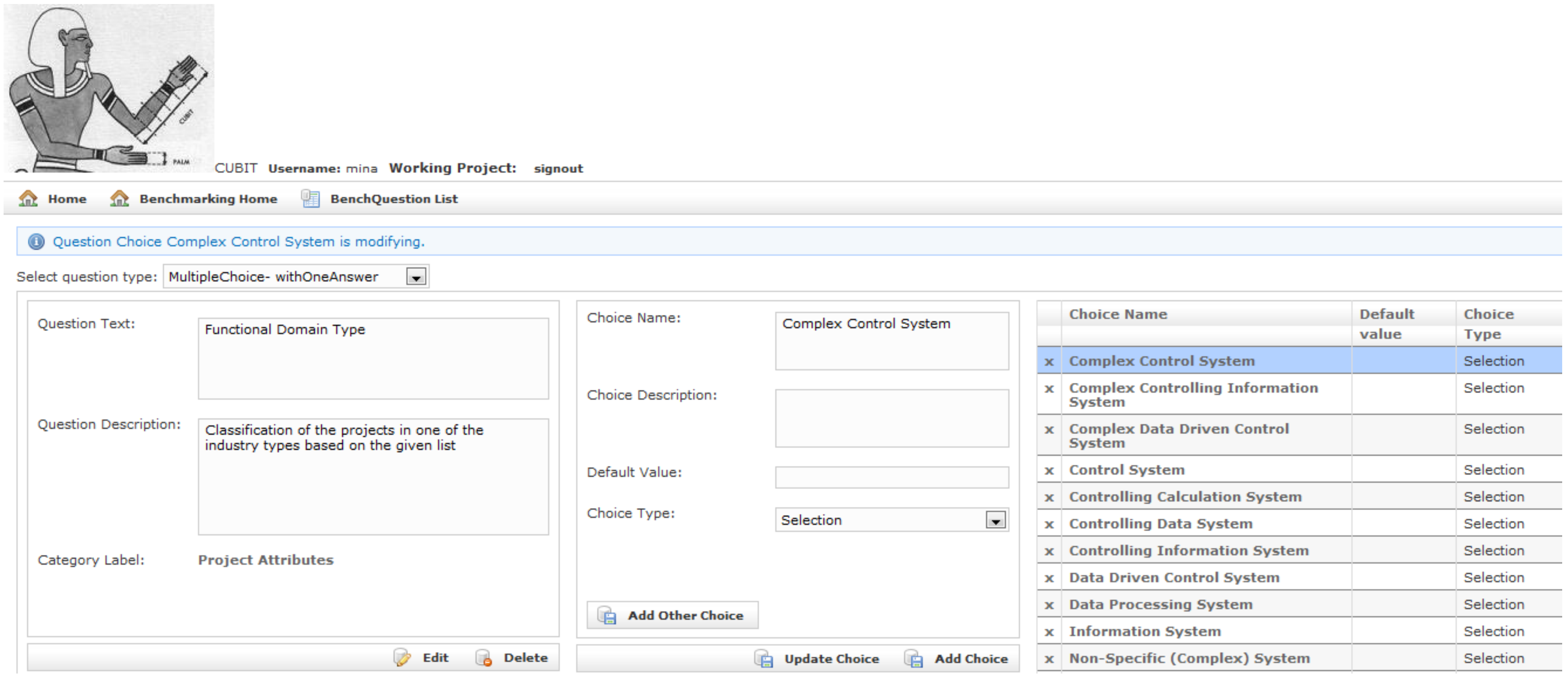
Question Text:	Effort for Requirements Definition Activities
Question Description:	effort in person hours for the requirements definition activities
Category Label:	Effort
Validation Format:	String

Choice Name:	
Choice Description:	
Default Value:	
Choice Type:	Text

	Choice Name	Description	Default value	Choice Type
x	**Software Requirements Analysis Activities**	to establish the requirements of the software elements of the system		CheckedText
x	**Stakeholder Requirements Definition Activities**	To define the requirements for a system that can provide the services needed by stakeholders		CheckedText
x	**System Requirements Analysis Activities**	To transform the defined stakeholder requirements into a set of desired system technical requirement		CheckedText
x	**Total Actual Effort Requirements Definition Activities**	Total actual effort in person hours for the requirements definition activities		Text

Figure 6 : Define MultipleTextbox Question

Figure 7 presents the “define multiple choice questions” with one answer GUI. This question type is designed for collecting benchmarking measures which one answer should be selected between several defined choices. In answer benchmarking questions the choices of this question are displayed as radio buttons. For instance, this question type is used for collecting “functional domain type” data which is depicted in Figure 7.



CUBIT **Username:** mina **Working Project:** **signout**

Question Choice Complex Control System is modifying.

Select question type: MultipleChoice- withOneAnswer

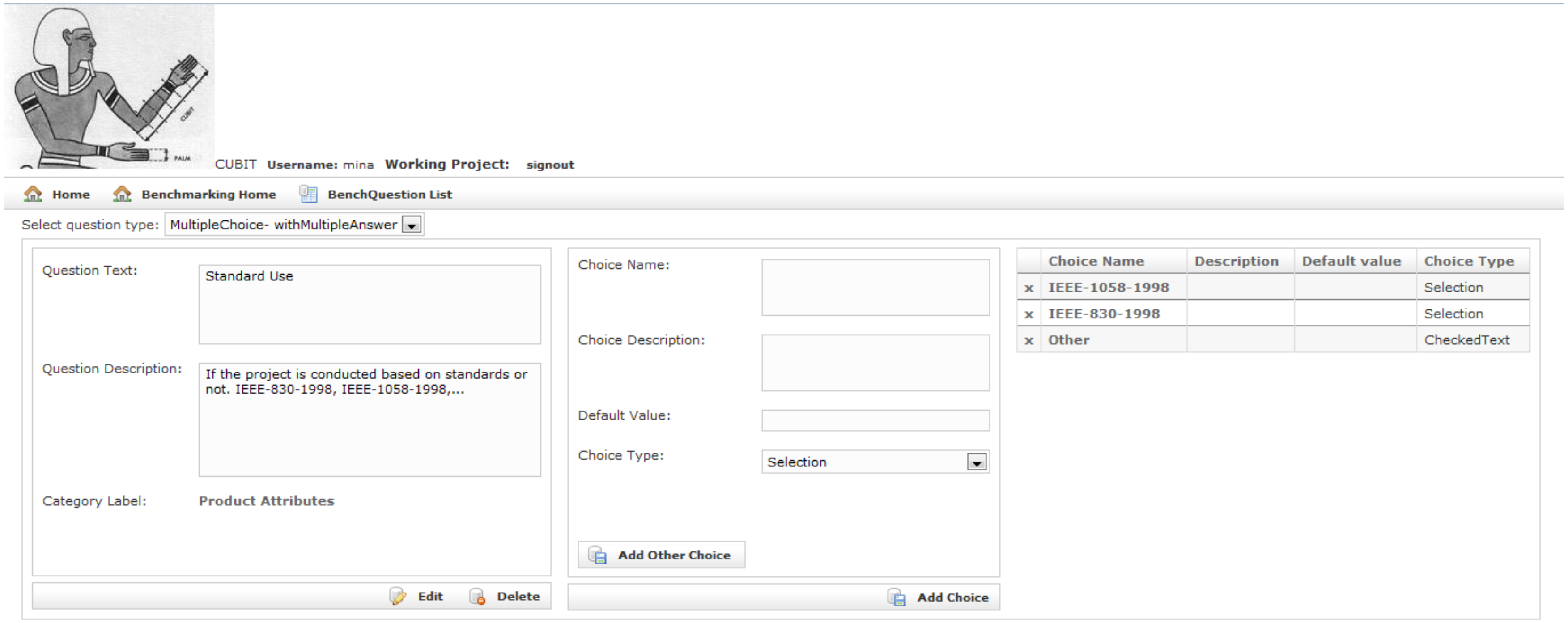
Question Text:	Functional Domain Type
Question Description:	Classification of the projects in one of the industry types based on the given list
Category Label:	Project Attributes

Choice Name:	Complex Control System
Choice Description:	
Default Value:	
Choice Type:	Selection

	Choice Name	Default value	Choice Type
x	Complex Control System		Selection
x	Complex Controlling Information System		Selection
x	Complex Data Driven Control System		Selection
x	Control System		Selection
x	Controlling Calculation System		Selection
x	Controlling Data System		Selection
x	Controlling Information System		Selection
x	Data Driven Control System		Selection
x	Data Processing System		Selection
x	Information System		Selection
x	Non-Specific (Complex) System		Selection

Figure 7: Define Multiple Choice with One Answer Question

Figure 8 presents the "define multiple choice questions" with multiple answers GUI. This question type is designed for collecting benchmarking measures which several answers can be selected between defined choices. As an example, this question type can be utilized in collecting "Standard Use" benchmarking measure data in product attributes category.



Select question type: MultipleChoice- withMultipleAnswer

Question Text: Standard Use

Question Description: If the project is conducted based on standards or not. IEEE-830-1998, IEEE-1058-1998,...

Category Label: Product Attributes

Choice Name:

Choice Description:

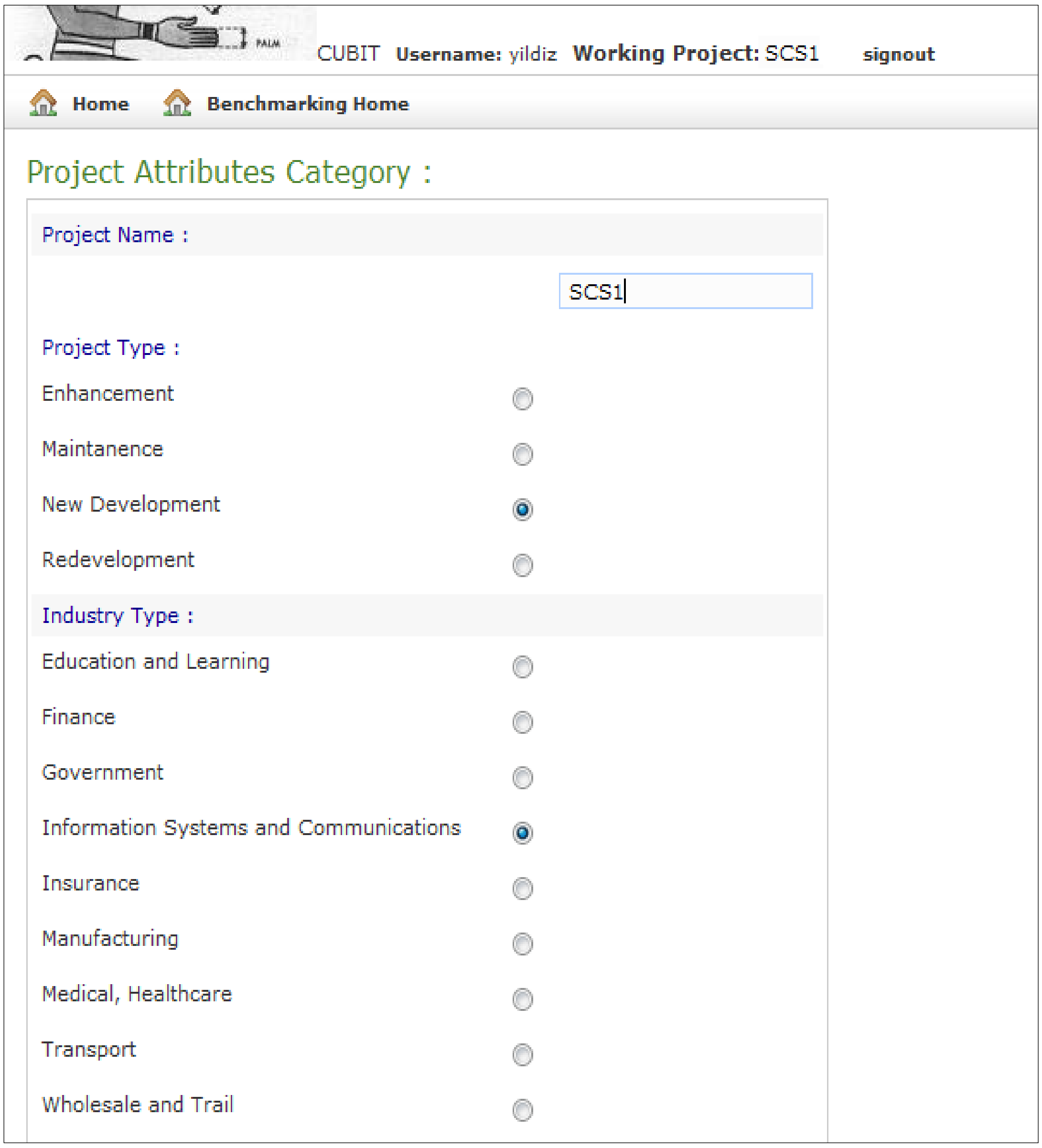
Default Value:

Choice Type: Selection

	Choice Name	Description	Default value	Choice Type
x	IEEE-1058-1998			Selection
x	IEEE-830-1998			Selection
x	Other			CheckedText

Figure 8: Define Multiple Choice with Multiple Answer Question

In the second stage the data submitter logs into the Cubit with specified user and password to answer the questions related to benchmarking. After selecting project from the list of projects, benchmarking questions are displayed according to question categories, and question orders. After answering benchmarking questions of each category, users use Next or Back buttons to navigate to the next question category or to the questions of previous question category respectively. In order to give information about each question, description of each benchmarking question according to defined benchmarking measures (section 3.1) is provided as a tooltip text when the mouse moves over questions. The answers for benchmarking questions will be validated (according to validation formats which explained) before saving them, and if any problem related to answers is found, the system will warn the user. Figure 9 presents the answer benchmarking questions GUI of Cubit benchmarking data collection tool.



Project Attributes Category :

Project Name :

SCS1

Project Type :

Enhancement ○
Maintanence ○
[✓ New Development]
Redevelopment ○

Industry Type :

Education and Learning ○
Finance ○
Government ○
[✓ Information Systems and Communications]
Insurance ○
Manufacturing ○
Medical, Healthcare ○
Transport ○
Wholesale and Trail ○

Figure 9: Answer benchmarking questions

CHAPTER 4

APPLICATION OF THE MODEL AND AUTOMATED BENCHMARKING DATA COLLECTION

This chapter describes the two case studies which are utilized to develop and validate the benchmarking methodology. In the first case study the requirements of developing benchmarking methodology and benchmarking measures is explored. Then, project data for the identified benchmarking measures are collected, and improvement opportunities for these benchmarking measures are investigated. As the result of this case study an automated benchmarking data collection tool is developed. In the second case study, our purpose was to validate the proposed methodology and benchmarking data collection tool. Benchmarking projects data for another organization were collected for this purpose and fill in ratios of benchmarking measures, productivity ratios of projects are examined. Also effort estimation models are constructed and evaluated.

In this chapter, research questions and research methodology is explained. Then case study design, plan, and case study results are described. Finally, in the last part the threats to the validity of the study are discussed.

4.1. Research Questions

The purpose of this study is to investigate improvement opportunity for efficient software benchmarking methodology by considering a meta-data model of project attributes for benchmark data repository and defining data collection processes. In this study the characteristics of available benchmark data sets were evaluated and the benchmarking measures were identified. Then processes for collecting data for these measures were identified. By considering identified benchmarking measures and benchmarking data collection processes, implementation of collecting benchmark dataset was the next target of this study.

In order to cover these purposes the following research questions were explored:

Q1: What are project attributes of a benchmarking meta-model which can be used in establishing reliable effort estimation models?

Q2: For the purpose of software benchmarking which measures can be collected in organizations in practice?

Q3: What are the requirements of automated benchmarking data collection processes which improves benchmarking data repositories?

Q4: Is this benchmarking methodology applicable to other organizations?

Q5: Does data collected by this methodology lead to better effort estimation?

We used qualitative research methodology to answer the research questions. There are several approaches in qualitative research: case study, Ethnography, Ethology, Ethnomethodology, Grounded theory, Phenomenology, Symbolic interaction, action research, and historical research. Among these nine approaches for answering the research questions, case study approach is selected in this study. We have selected case study approach since we wanted to do detailed exploratory investigations to get more insights for the causes of inaccuracy of benchmarking data repositories, and we do not have any control on behavioral events and variables.

4.2. Case Study Design

Two case studies were conducted to explore the answers for the research questions.

In the first case study, an exploratory study was conducted to find the benchmarking data attributes and benchmarking data collection processes in the literature. The first, second, and third research questions were answered in this case study. In order to find benchmarking measures available benchmarking data repositories were examined and evaluated and benchmarking measures and benchmarking data collection processes were identified for software benchmarking purpose. Subsequently, in this case study projects data which were collected from an organization based on these identified benchmarking measures were evaluated and improvement possibilities for the identified measures and benchmarking data collection processes were investigated by using these data. Meanwhile, the third research question was answered in this case study and as a result of this case study an automated benchmarking data collection was integrated to Cubit. Also, a project data were collected from another company in order to observe collection potential of benchmarking measures and get more insight about quality of projects data.

At the end, in the second case study validation of the automated benchmarking data collection tool was performed and fourth and fifth research questions were answered in this case study. This automated tool is validated by using benchmarking project data to investigate whether benchmarking project data leads to better effort estimation or not.

4.2.1. Case Selection Criteria and Background of these selected cases

The cases which were used in the both case studies were gathered by researchers in researches in Software Management Research group (http://smrg.ii.metu.edu.tr/smrgp/). The first case projects data were from organization projects data of banking domain and also a project from communication domain. The second case was from project data of an organization in different domain. These three organizations were selected in order to be able to generalize the results of the study for organizations of wider domains. On the other hand since we were conducting other projects with the organizations from these domains it was easy to reach information of benchmarking project data in these three organizations.

4.3. Case study 1: Exploratory Case Study

In this case study software benchmarking measures which can be used in constructing reliable effort estimation models, and requirements of benchmarking data collection tool are explored. In order to find these measures and requirements first literature review was conducted. As the result of this survey benchmarking measures, and data collection processes were determined for benchmarking purpose. Projects data were collected from three organizations to find improvement opportunities for this identified approach. Lastly after refining these measures and processes, benchmarking data collection tool is automated as a part of proposed benchmarking methodology.

4.3.1. Case Study 1 Plan

The activities which were included in case study 1 were determined in the case study plan. Detailed activities of this plan are as follows;

- Planning the literature survey to evaluate available benchmarking data repositories.
- Identifying benchmarking project attributes which were used in available benchmarking data repositories, and selecting benchmarking measures which can be collected from software organizations in practice.
- Planning Literature survey to identify benchmarking data collection processes used in data collection of available data repositories and refine these processes in order to improve the quality and reliability of benchmarking data set.
- Selecting projects from an organization which includes benchmarking data and applying measures on the selected projects to collect benchmarking project data.
- Analyzing benchmarking project data in order to find problems and biases related to gathered data. In this step after detection of problems of benchmarking project data, problem resolution will be done.
- Tailor the benchmarking measures and processes based on results of analyzed data and proposed problem resolutions.
- Collecting a sample project data from another company to get inside about quality of collecting data
- Developing tool support for benchmarking measures and data collection processes.

4.3.2. Case Study 1 Conduct

The first step in this case study was literature review on external software benchmarking data repositories from effort estimation perspective. Benchmarking data repositories which were utilized in software engineering research studies were selected in this evaluation. The selection criteria for benchmarking datasets were the accessibility of the repository data or availability of total software size and total project effort in the data repository. 14 data repositories which are shown in Table 2 were selected for this evaluation.

Table 2: Data Repositories Evaluated in This Study

Name of the Data Repository	Data Reference
1. ISBSG	International Software Benchmarking Research Group
2. CSBSG	Chinese Software Benchmarking Standards Group
3. IPA/SEC	Information-Technology Promotion Agency/ Software Engineering Center
4. Albrecht Repository	By Yanfu and Keung
5. China Repository	By Fang
6. Desharnais Repository	By Desharnais
7. Finnish Repository	By Keung
8. Maxwell Repository	By Yanfu
9. Kemerer Repository	By Keung
10. COCOMO81	by Barry Boehm
11. NASA93	By Jairus Hihn
12. COCOMO SDR	In the form of COCOMO by SoftLab
13. Miyazaki94	By Amasaki
14. COCOMO_NASA	In the form of COCOMO by NASA

Data repositories are evaluated from four different perspectives: general features, properties of data collection processes, properties of data quality and data validation processes, and project characteristics of data repositories (Ozantop, Nabi, & Demirors, 2011). In general features point of view, general information such as geographic origin, the initiated date, data availability, and other general information about data repository are studied. Meanwhile, properties of data collection processes provide information about how and from which sources data is collected. Properties of data quality and data validation processes give information about reliability of data in the data repository which is an indication of quality of data repository itself. These properties are not kept in the data repository itself, but they give useful information about data repository's features. Lastly, in project characteristics of data repositories, attributes which are factor drivers for effort estimation were identified

and examined in these datasets. Details about this study can be found in technical report (Ozantop, Nabi, & Demirors, 2011).
In the project characteristics we examined existence of factor drivers for effort estimation such as actual effort, size of software, duration of the project, team experience, team size, software domain, programming language, hardware platform and the usage of standards through the software development processes. All of the data repositories contain size and effort data, but only half of these data repositories provide information about team experience level. It can be observed that, although software domain and effort data are important in effort estimation, only some of the data repositories provide these data (Ozantop, Nabi, & Demirors, 2011).
Size and effort data are most important data in effort estimation, so we evaluated the existence of detail level of these data in data repositories.
Size data in ISBSG has been collected in IFPUG, COSMIC, MarkII, NESMA, FISMA, and LOC forms. BFC of IFPUG and COSMIC are available in ISBSG, but just the total numbers are available. However, it was expected that all the measurement data will be available to the users of the repository. Also, total effort and phase effort data for each phase of software development lifecycle in person-hours has been provided in ISBSG. Only for small numbers of projects the amount of added, changed and deleted functions is available (Ozantop, Nabi, & Demirors, 2011).
Size data is collected in more details in IPA/SEC than ISBSG. Both planned and the actual size and effort are available in IPA/SEC. Effort and size data is given for each phase of software development life cycle. Besides, other data like numbers of pages of documents, number of screens, number of data flow diagrams, and use cases are given as a size indicator (Ozantop, Nabi, & Demirors, 2011).
Because raw data of CSBSG data repository is not available, it couldn’t be evaluated from project characteristics perspective. Among remaining 11 data repositories, only Alberta and China data repositories includes functional size data in BFC level, and other data repositories contain only single size data. Effort data in none of these 11 data repositories are given for phases of software development (Ozantop, Nabi, & Demirors, 2011). Summary of existence of project attributes are given in table 3.

Table 3: Project Attribute Existence of the Repositories

Name of the Repositories	Actual Effort	Size	Team Experience level	Duration	Domain of SW	Programming Language	HW Platform	Std. Usage Info
ISBSG	+	+	+	+	+	+	+	+
IPS/SEC	+	+		+	+	+	+	
CSBSG	+	+		+	+	+		
Albrecht DS	+	+						
China DS	+	+		+				
Desharnais DS	+	+	+	+		+		
Finnish DS	+	+						
Maxwell	+	+	+	+	+		+	+
Kemerer	+	+		+		+	+	
COCOMO 81	+	+	+					
COCOMO NASA	+	+	+					
COCOMO SDR	+	+	+					
Miyazaki 94	+	+						
NASA 93	+	+	+		+			

After literature survey, 11 projects were selected by researches from an organization in order to investigate which benchmarking data attributes can be collected in practice in the organizations considering project attributes of data repositories. Project type of 5 projects out of these 11 projects, were “New development” and the remaining were “enhancement”.

Projects data was collected by interview and data collection forms in excel document was utilized for this purpose. Initial collection forms are constructed by considering ISBSG (2009) and IPA/SEC (2004) data repositories. Researchers attempted to collect project data under about 70 project attributes in the first attempt, but we (as researcher) found out that some of these benchmarking attributes cannot be collected in practice from organizations, so these attributes were eliminated, or refined in order to find more practical measures for benchmarking purpose. Based on these observation researchers published a benchmarking attribute definition in Ozcan Top and Demirors (2011) technical report. Benchmarking attributes of this benchmarking attribute definition document were considered as a base in this study, and further investigation and inspection were conducted to refine these measures.

The next task in the case study was analyzing benchmarking project data in order to improve benchmarking measures. Projects data were examined from several aspects in this evaluation and also for further inspection we calculated the productivity ratios of the projects. Some problems were detected during and after data collection, which are listed below;

- There were missing data in projects data.
- Sum of number of Entries, Exits, Reads, and Writes were not equal to total COSMIC functional size.
- Sum of the effort data of phases was not equal to the total effort.
- There were some effort records which were not in the identified effort category of benchmarking attribute.
- There were variances in productivity ratio of projects.

For solving these problems in the data base, we undertook some actions. First, missing data of any benchmarking attributes were asked for resubmission. Second, functional size measurement of these projects were examined by experts to detect any problem in the measurement. In the case of any problem, the measurements of these projects were corrected by experts who have COSMIC FSM certification and three years measurement experiences. Then, functional size of the projects was updated in benchmarking data. Third, effort data were examined for inaccuracy, and we investigate the reasons of this inaccuracy. We found out that some effort data are not kept in the organization in detail in the effort record, and only total effort of the project is recorded. In some other cases effort records do not match any identified effort category in the benchmarking attributes, and there was not any clear process definition for effort data collection. Obviously, a need for defined data collection process definition was observed in this problem. Finally, productivity values of these projects were inspected and In order to find the reasons of variances in productivity ratio, projects data were studied thoroughly in detail. Productivity ratios of projects are given in table 4.

Table 4: Productivity ratio (Person-hours/FP)

Project	**Project Type**	**Total Effort/Size ratio**
A	Enhancement	3.887323944
B	New Development	2.539325843
C	Enhancement	13.66666667
D	Enhancement	6.588235294
E	Enhancement	1.473684211
F	Enhancement	0.641975309
G	Enhancement	3.151515152
H	New Development	11.62189055
I	New Development	8.342857143
J	New Development	2.759358289
K	New Development	5.388174807

As a first remark, large variances were observed in effort/size ratios. We detect outliers by using plot box analysis (Field, 2009) by using SPSS program. In order to inspect the reasons of these outliers, projects' data were examined more precisely. There are some studies which depict functional similarity as significant impact on the relation of functional size and software development effort (Santillo & Abran, 2006) (Tunalilar et.al, 2008) (OzanTop O., 2008) (OzcanTop et.al, 2009) (Tunalilar, S., 2011). So, functional similarity issue was taken into account in this inspection.

The first outlier had a large effort/size ratio, and the project was an enhancement project and it was related to implementation of new electronic fund transfer standard which had complicated business rules. This project was apparently different than other projects of the organization, and it needed intense requirement analysis activity, because in order to discuss business rules of this project a lot of meetings had to be held. On the other hand, because of security issues for small changes in the system, a long duration of testing activities had to be done. The second outlier had also large effort/size ratio, and the reason behind this abnormal case was high amount of testing activities which were performed for this project. The third outlier project had a small effort/size ratio, because this project was an enhancement project which includes small changes and the functional similarity was very high in this project. Consequently, functional similarity reflective size was very small and less effort was required for this project. The forth outlier had also small effort/size ratio, and similarly high functional similarity. So, functional size reflective size was small and development effort for this project reduced intensively.

In order to improve benchmarking measures functional similarity reflective size was considered as project attribute, and for finding this reflective size as mentioned before it is important to make sure that details of COSMIC functional size measurement are available. Also, in order to find more homogenous project in benchmarking process, an explanation for project specific characteristic should be collected during collecting benchmarking data. For instance, when a project has different characteristic revealing them will help in selecting homogenous projects.

After these observations, all of these improvement opportunities were considered and defined benchmarking measures were updated respectively.

A project data from a small size company was also collected. We observed that in this company effort data is not recorded in daily or even in weekly bases, and during interview data submitter only provided us with overall consumed time for main phases of the project with best guess. As it is indicated before, quality of data play critical role in quality of benchmarking data repository. So, we classified projects data quality based on the quality of effort data. In the first data quality level (A) effort data are recorded in daily bases by using effort data collection tool support, time sheet, etc. In the second project data quality level (B) effort data are collected in weekly or monthly level without using tool support. Finally, in the third quality level (C) effort data are not recorded, and only by best guess of the project manager can be collected.

Benchmarking data collection processes as well as quality of the data are beneficial in insuring the quality of data. So, as another improvement of benchmarking, data collection processes which were identified in OzcanTop and Demirors (2011) technical report are selected, and refined in this study.

By considering defined benchmarking measures, and benchmarking data collection processes which are given in chapter 3, a benchmarking data collection tool were implemented in order to seize improvement opportunity for benchmarking. This benchmarking data collection tool is integrated on Cubit as a third and final part of benchmarking methodology which is proposed in this study. The features of the tool were discussed in chapter 3 section 3.

4.3.3. Case study 1 Results

In this case study our aim was identifying and defining requirements of benchmarking methodology which includes benchmarking measures, benchmarking data collection processes, and automated benchmarking data collection tool. By using literature survey important benchmarking measures were identified and the practicability of collecting these measures was investigated by examining 11 projects from an organization. The problems and inconsistencies were identified to refine benchmarking measures. Also, data collection processes which were defined in Ozantop and Demirors (2011) technical report were selected as benchmarking data collection processes. After refining measures and data collection processes finally, automated benchmarking data collection tool were integrated on Cubit.

COSMIC functional size is used as size measurement method for measuring functional size of these 11 projects, and projects' detailed functional measurements were measured and collected by experts. We observed that collecting detailed functional measurement were necessary in order to calculate functional similarity which had very large impact on effort/size ratio variances. So by considering (Ozcan Top O., 2008) and previous implementation of functional similarity measurement for cosmic FSM method by B. Usgurlu (2010), reflective functional similarity measurement was integrated to the new version of Cubit.

Also we observed that quality of effort data play critical role in quality of benchmarking data repository by examining project data of another company. Since in this company effort data are not collected in daily, or even weekly bases for each defined activities and only approximated effort data are available, so we classified this project data in C level.

It should be mentioned that effort data are considered in two levels: activities and sub activities. Activities are defined as core benchmarking measures, and sub activities are defined as extended benchmarking measures. We know that effort data are not recorded in such a detail in most of companies, but we suggest that recording these effort data in sub activity bases will lead to more accurate effort data, and in result we conclude in more accurate benchmarking data repositories.

Collecting data via this benchmarking tool enable the user to collect benchmarking measures by following defined benchmarking process. In collecting benchmarking data answers for benchmarking attribute data is validated by utilizing validation format of each answer in Cubit. Besides, description of each benchmarking measure is provided to the user as a tooltip text when the mouse moves over the benchmarking questions. This feature provides users with extra information about the benchmarking measures. In this case, projects data will be gathered in more reliable and accurate way by validating both benchmarking data and size measurement of the projects. Besides, collecting data via data collection forms and questionnaires takes a lot of effort and time for both collecting and validating data, but collecting benchmarking project data with tool support will reduce this time and effort.

4.4. Case study 2: Validation of the Benchmarking Methodology and Automated Benchmarking Data Collection Tool

This case study is designed to investigate the validity of benchmarking methodology and explore the answers for fourth and fifth research question. In this case study in order to validate the benchmarking methodology, benchmarking projects data were collected by using benchmarking data collection tool Cubit from an organization. Subsequently, productivity ratio of collected projects were inspected in detail, and by using linear regression models and multiple regression models effort models were constructed to evaluate the benchmarking data which is collected by the support of benchmarking data collection tool.

4.4.1. Case Study 2 Plan

The activities which were planned to be done in case study 2 were determined in the case study plan. Detailed activities of this plan are as following;

- Selecting projects from an organization for the purpose of collecting benchmarking data
- Collecting benchmarking data of selected projects by using Cubit, considering defined benchmarking data collection processes.

- Analyzing and inspecting benchmarking projects data
- Using collected projects data for constructing effort estimation models by using regression models, and calculating MMRE and PRED values for validation of the quality of the benchmarking project data.

4.4.2. Case Study 2 Conduct

In this case study 40 projects data from another organization utilized for the validation purpose. Benchmarking data were collected by using benchmarking data collection tool (Cubit) and interviewing with data submitter. These projects belong to three different functional domain types: Simple Control System (SCS), Complex Control System (CCS), and Complex Data Driven Control System (CDDCS). These functional domain types are identified based on Char Method. Corresponding software type of these projects based on ISO12182 standard for software categorizations are real time embedded device driver, real time embedded avionics message router, and process control system respectively. All project type of these projects was "New development".

Collected projects data was analyzed from several points and accuracy of these data were evaluated. In order to perform data analyses, fill in ratio for the entire benchmarking data attributes were calculated, and also derived attributes such as productivity ratio and functional similarity were examined thoroughly.

We observed that fill in ratio for project type, industry type, functional domain type, tool use, experience of team members, stability of team, all attributes in product attributes category, Effort (for requirements, design, coding, and testing activities), and detailed size data are 100%. Also there were some effort record which can be used as an extension of our effort attributes.

Also we inspected size/effort ratio, and we observed that size/effort varies between 0.03 FP/Person-hours and 3.47 FP/Person-hours. When we consider functional similarity as we expected, this variance decreased, and the size/effort ratio differed from 0.01 FP/Person-hours to 1.66 FP/Person-hours. Because as mentioned before, projects data was from three different application types, each of which were developed under similar conditions by the same team. So, we expect size/effort ratio values will be similar for each group of projects. When we consider functional similarity and recalculate the size/effort ratio, the variance in these values decreased. In Table 5 the size/effort ratios before considering functional similarity and after considering functional similarity are given for projects which had functional similarity.

Table 5: Size/Effort ratio for functional similarity consideration

Project Name	**Size**	**Total Effort (person hours)**	**Size/Effort before FS**	**Size/Effort after FS**
SCS 1	411	784	0.524235	0.512755
SCS 2	1730	3768	0.45913	0.429936
SCS 5	165	2192	0.075274	0.061588
SCS 7	319	1952	0.163422	0.099898
SCS 9	149	1848	0.080628	0.069264
SCS 10	249	808	0.308168	0.241337
CCS1	2040	2928	0.696721	0.556694
CCS 2	245	5568	0.044001	0.035022
CCS 3	361	1112	0.32464	0.258094
CCS 4	55	1736	0.031682	0.011521
CCS 5	38	1152	0.032986	0.028646
CCS 6	470	2872	0.163649	0.082869
CCS 8	271	1224	0.221405	0.215686
CCS 9	162	904	0.179204	0.167035
CCS 10	50	816	0.061275	0.042892
CDDCS 1	584	1020	0.572549	0.357843
CDDCS 2	1347	396	3.401515	0.997475
CDDCS 3	415	476	0.871849	0.684874
CDDCS 4	1303	376	3.465426	1.659574
CDDCS 5	129	232	0.556034	0.392241
CDDCS 6	76	248	0.306452	0.237903
CDDCS 7	986	536	1.839552	0.451493
CDDCS 8	1384	832	1.663462	0.25

Table 5: Size/Effort ratio for functional similarity consideration (Continued)

Project Name	Size	Total Effort (person hours)	Size/Effort before FS	Size/Effort after FS
CDDCS 9	132	96	1.375	0.125
CDDCS 10	277	208	1.331731	0.591346
CDDCS 11	193	224	0.861607	0.348214
CDDCS 12	377	792	0.47601	0.222222
CDDCS 13	291	356	0.817416	0.688202
CDDCS 14	328	1020	0.321569	0.191176
CDDCS 15	666	536	1.242537	0.225746
CDDCS 16	332	616	0.538961	0.387987
CDDCS 17	206	476	0.432773	0.344538
		Variances	**0.738**	**0.11**

Although by considering functional similarity we were able to reduce the variance in Size/Effort ratio, we still encounter some outliers in these data. In order to improve our data quality, we inspected productivity ratios for all projects in more detail. Examining outliers in these ratios revealed some facts about the projects' characteristics. Most of projects with outlier data had algorithms which could not be measured by using COSMIC measurement size method. We hypothesized that the existence of these algorithms increased the amount of effort used in these outlier projects. Since we couldn't reach source code of these projects to indicate Cyclomatic complexity or other complexities, we tried to classify algorithm complexity to three levels;

1. Basic Algorithms (Level 1): Small algorithms include only basic mathematical calculations and simple data manipulations which are: Derived data creation by transforming existing data, Mathematical formulas/calculations, Condition analysis to determine which are applicable, Data validation, Equivalent-value conversion, and Data filtering/selection by specified criteria. This classification of data manipulation is adopted from action type list defined in Santillo & Abran (2006).

2. Medium Complex algorithms (Level 2): Algorithms in this level include medium complex algorithms which have different operations than defined action type above (defined in the basic algorithms), and in these algorithms there isn't any integration with other algorithms in the system. Also, in this kind of algorithms there isn't parallel and multitasking usage of processes. In this level the input of algorithms are a group of parameters, and the result of medium complexity operation can be one or several outputs.
3. Very complex algorithms (Level 3): Algorithms which includes very complex operations, and there is integration with other algorithms. In this kind of algorithms extra hardware are involved. In addition, in this kind of algorithms, there are real time criteria as limitation factors.

We requested from data submitter to classify algorithms of the projects and classify projects based on these levels. It was observed that most of the outlier projects had algorithms in very complex algorithms level.

Following these inspections, effort estimation models were constructed by using IBM SPSS software, and simple linear regression models were utilized to determine usability of proposed benchmarking data collection model. Effort data was considered as dependent variable, and size data considered as independent variable. The total and development effort of projects in this case study was estimated by considering functional domain types, and functional similarity. Meanwhile, effort for main activities in software development lifecycle was estimated. For creation of these models we used total functional size of the projects. In order to evaluate constructed effort estimation models, MMRE and prediction level parameter PRED(30) values were used in this study as presented in Equation 1 through 3. There are studies which uses PRED(30) to measure how well the estimation model is performing (Menzies, et al., 2005). Meanwhile, PRED(30) can identify the prediction models which are generally accurate (Menzies, et al., 2006). A low MMRE and high PRED value indicate how well an effort estimation model can perform. PRED(N) means the average percentage of the estimation values is within N percentage of actual values. For instance, PRED(30) =50 means that 50% of the estimates are within 30% of the actual values (Menzies et.al, 2006).

$$\mathbf{MMRE} = \frac{100}{T} \sum_{i}^{T} |\mathbf{estimated_i} - \mathbf{actual_i}| / \mathbf{actual_i} \qquad \textbf{(Equation 1)}$$

$$\mathbf{PRED(N)} = \frac{100}{T} \sum_{i}^{T} \begin{Bmatrix} 1, if\ MRE_i \leq \frac{N}{100} \\ 0, else \end{Bmatrix} \qquad \textbf{(Equation 2)}$$

$$\mathbf{MRE_i} = \sum_{i}^{T} |\mathbf{estimated_i} - \mathbf{actual_i}| / \mathbf{actual_i} \qquad \textbf{(Equation 3)}$$

We also used effort estimation models of 7 data repositories (Albrecht, China, Desharnais, Finnish, Maxwell, Kemerer, and ISBSG) in order to compare accuracy of estimations from our previous study (OzcanTop et.al, 2011). The selection criteria for data repositories were related to availability of raw data, and also availability of functional size and effort data. Among these data repositories ISBSG was the only data repository which includes size data measured by COSMIC method.

Effort estimation models can differ based on selection of different subset of projects data in data repositories which subsequently influence the accuracy of the model. Also, pruning of the data can improve the effort estimation model (Maxwell, K., 2001). In Ozcan Top et.al (2011) a systematic pruning was utilized to eliminate unrelated data. The regression model of previous mentioned data repositories and effort estimation model for total effort of our case study projects data are shown in Table 6.

Table 6: Estimation model of 7 discussed data repositories and case study projects data

Model	**Number of Projects**	**Mean of FP**	**Regression Model**	**MMRE**	**PRED(30)**
Albrecht	14	347	E= -1387.4+ (29.3*FP)	4006.6	0
China	398	189	E= 418.8+ (9.4*FP)	2167.3	0
Desharnais	73	243	E= 156.1+ (16.7*FP)	3802.5	0
Finnish	15	273	E= 553.3+ (7*FP)	426.2	0
Maxwell	40	274,5	E= -255.6+ (17.6*FP)	5277.8	0
Kemerer	4	317,3	E= 172.6+ (1.1*FP)	162.7	0
ISBSG	151	134,5	E= 2095.9+ (13.8*FP)	137.0	0
Case Study 2 Projects data	40	435.62	E= 1091.442 + (0.428*FP)	136.995429	22.5
Case Study 2 Projects data (considering functional similarity)	40	287.19	E= 737.298 + (1.45*FP)	95.27	37.5

According to Table 8, linear models built by ISBSG, Albrecht, China, Desharnais, Finnish, Maxwell and Kemerer repositories do not create models with acceptable level of MMRE and PRED values. Also, our case study project data do not produce acceptable results for estimating total effort because a good model is expected to have PRED (30) higher than 60% (Tunalilar, S., 2011). Since the model which produce highest PRED(30) and lowest MMRE is considered the best, using our case study project data resulted better estimation model, and the effort model quality was improved. Meanwhile by considering functional similarity, PRED value for total effort was increased and MMRE value was decreased again.

We also constructed different effort estimation models for the selected organization to observe effect of functional domain type, and functional similarity in quality of estimation models. Both COSMIC size data without functional similarity consideration, and reflective functional similarity size data was utilized in model developments. The results of MMRE and PRED value for total and development effort models are given in table 7.

Obviously it can be seen that effort estimation models which were based on development effort produced better estimation, since the PRED values are higher and MMRE values are lower than those which were constructed using total effort. Also, when projects data are grouped by similar functional domain type it results in better estimation models. As discussed before, the projects of this case study belongs to three different functional domain type; Simple Control System (SCS), Complex Control System (CCS), and Complex Data Driven Control System (CDDCS) which are identified based on CHAR method. In addition to these observations, it can be distinguished from the table that considering reflective functional similarity size improves quality of effort estimation models.

In this study effort data is proposed to be collected in activities bases, so in order to validate this idea, effort estimation models were constructed for each activities in software development lifecycle. Comparison table of MMRE and PRED values of these models are given in table 8.

Table 7: MMRE and PRED (30) values for comparison of accuracy of effort estimation models for total and development effort

	Total Effort				**Development Effort**			
	No FS		**Reflective FS**		**No FS**		**Reflective FS**	
	MMRE	**PRED (30)**	**MMRE**	**PRED (30)**	**MMRE**	**PRED (30)**	**MMRE**	**PRED (30)**
Total Projects in case study	136.99	22.5	95.27	37.5	110.04	27.5	93.5	35
Project data with Simple Control System (SCS) Functional domain type	45.13	45.45	46.40	45.45	31.11	54.54	28.54	55.55
Project data with Complex Control System (CCS) Functional domain type	54.30	33.33	55.86	33.33	39.74	30	38.42	33.33
Project data with Complex Data Driven Control System (CDDCS) Functional domain type	63.22	41.17	51.21	31.25	54	41.17	46.13	52.94

Table 8: MMRE and PRED (30) values for comparison of accuracy of effort estimation models for software development activity efforts

	Requirements Activities				Design Activities				Coding Activities				Testing Activities			
	No FS		Reflective FS		No FS		Reflective FS		No FS		Reflective FS		No FS		Reflective FS	
	MMRE	PRED	MMRE	PRED	MMRE	PRED	MMRE	PRED	MMRE	PRED	MMRE	PRED	MMRE	PRED	MMRE	PRED
All Projects in case study	127.24	25	129.39	20	148.91	25	146.62	22.5	69.44	28.57	53.91	38.88	194.84	27.5	148.34	35
SCS projects	59.98	45.45	59.02	45.45	118.45	36.36	109.59	40	37.36	55.55	37.12	60	27.68	54.54	24.45	66.66
CCS projects	26.24	66.66	23.30	88.88	67.16	50	68	58.33	131.38	8.33	105.5	27.27	51	33.33	50.27	33.33
CDDCS projects	67.89	35.29	65.40	35.29	79.22	23.52	76.06	23.52	51.11	47.05	35.02	50	104.06	35.29	82.35	41.17

It can be easily seen that effort estimation based on software development activities can improve the accuracy of effort estimation model. Also, considering functional similarity and functional domain type are two other ways for increasing quality of benchmarking projects ‘data.

We also constructed multiple regression models by considering base functional components (Enter, Exit, Read, and Write) of COSMIC size as independent variables, and effort of activities in software development lifecycle as dependent variables. We categorized projects based on functional domain type. Here our purpose was to observe impact of collecting effort data in activities bases, and size data in base functional components, and considering functional domain type, and functional similarity all together. Comparison table of MMRE and PRED values of these models are given in table 9.

Table 9: MMRE and PRED(30) values for comparison of accuracy of effort estimation models for software development activity efforts by considering BFC of size data

	Requirements Activities		**Design Activities**		**Coding Activities**		**Testing Activities**	
	MMRE	**PRED**	**MMRE**	**PRED**	**MMRE**	**PRED**	**MMRE**	**PRED**
All Projects in case study	123.9	25	133.7	37.5	44.87	33.33	133.74	32.43
SCS projects	26.89	72.72	88.49	36.36	18.78	81.81	17.56	81.81
CCS projects	18.09	83.33	31.58	58.33	41.19	45.45	33.55	50
CDDCS projects	42.88	50	54.69	33.33	29.09	62.5	53.22	47.05

As it can be seen in table, when we categorize projects by functional domain type we can create better estimation models rather than constructing model for all projects in the case study. We observed that MMRE values decreased and PRED(30) values increased significantly by considering functional domain type, effort in activities level, size in BFC level, and functional similarity.

4.4.3. Case study 2 Results

In this case study in order to validate benchmarking data collection methodology 40 projects data were collected from an organization by using Cubit benchmarking data collection tool. Then projects data were inspected thoroughly by considering productivity ratios and fill in ratio of benchmarking attributes. Lastly, effort estimation models of collected data were constructed by using simple linear regression model, and compared to effort estimation models of other data repositories. Also effort estimation models for total effort, development effort, and each activities of software development (requirements, design, coding, and testing activities) are constructed. Meanwhile, effect of functional domain type and functional similarity were evaluated in effort estimation. In order to compare the accuracy and quality of effort estimation models MMRE and PRED (30) values were used. As it mentioned before, A high PRED (30) and low MMRE value can indicate the quality of prediction model.

In productivity ratio examination, there were some outliers. Because projects data were from three different functional domain types and they were developed by the same team. In similar situations, we expected effort/size ratio for projects with same functional domain type to be same. So, we investigated the reason of these unexpected outliers. We found out that projects with outlier productivity ratio have complex algorithm used in them. In order to interpret this fact, we tried to categorized project data into three different complexity levels of Basic Algorithms, Medium Complex Algorithms, and Very Complex Algorithms by interviewing the data submitter. When projects data ranked to three level of complexity, we observed that projects with outliers mostly have several algorithms with Very Complex Algorithms level of complexity.

Continuing productivity ratio inspection, we encounter some projects which had large total effort/size ratio. The reason behind these abnormal projects data were from projects characteristics. Projects were from functional domain type in which hardware is included, and they are designed for special control functions within a larger system. In some of the projects, developer was not familiar with hardware which is used in these systems and new hardware was used in these projects. The project submitters informed us that it takes more time to be familiar with setting of new hardware, thus, developing these projects needed more effort.

In addition, in this organization there were some effort records which are not classified under software development effort, and they include effort data for documentation, ideal effort time, and standard application effort time. Ideal effort includes the times when there is not any activity on the project, for example when there is a problem with hardware and the developers wait for solving this problem. Although there is no effort consumed on the project, but the developer records this waiting time as ideal effort. Meanwhile, in some projects, projects should be developed under a specific standard and applying this standard caused extra testing effort which included in total effort of these projects. We observed that in outlier projects these effort records resulted in large total effort, and accordingly large effort/size ratio.

After these assessments, effort estimation models were evaluated. We observed that constructing effort models for development effort and each activity in software development lifecycle produces better estimation models than total effort. Also, results showed that, classifying projects data based on functional domain type and constructing effort models for projects with similar functional domain type produces effort models with higher PRED(30) and lower MMRE values which means better quality in effort estimation.

In addition, collecting size data in BFC level of COSMIC functional size measurement method leads to creating better estimation models. As the last observation, considering functional similarity and functional reflective size improved the accuracy of effort estimation models.

The results of this case study showed that using benchmarking methodology, we can improve benchmarking data repositories quality from effort estimation perspective. It should be mentioned that, in this organization we collect data of finished projects by considering benchmarking measures and using benchmarking data collection tool. But benchmarking data collection processes were not pursued from the beginning of projects to the end, so we believe if the defined benchmarking data collection were followed in this organization, we would end up with better results.

4.5. Validity Threats

During collecting benchmarking data collection, functional size measurement details of the projects were collected in excels documents, and it may include some errors. To detect the errors reviews were conducted by experts who have COSMIC FSM certification and three years measurement experiences.

Projects data for effort attributes are collected by interviews and they are assumed to be accurate. For the resolution of this threat using automated data collector is considered as future work.

Finally, we only investigate impact of algorithm complexity in one organization, and generalizing the impact of this measure should be investigated more.

CHAPTER 5

CONCLUSIONS

This chapter summarizes the contributions of the study, and presents suggestions for future works.

5.1. Conclusions

In order to plan, monitor, and control the project activities, effort estimation of software projects is an essential step for success of projects. In all diverse estimation methods, historical data (benchmarking data sets) are necessary elements for developing estimation models. So, accuracy of benchmarking data is critical for construction of reliable effort estimation models. In many studies effective effort estimation methods were studied, but a few of them considered quality of historical data as an impact on effort estimation accuracy.

We developed a benchmarking data collection methodology to improve quality of benchmarking data repositories. This approach consisted of three main parts; Benchmarking measures, benchmarking data collection processes, and automated benchmarking data collection tool. In order to build reliable benchmarking data repository, projects data attributes and characteristics were defined precisely. We observed that quality of benchmarking data repositories does not only depend on benchmarking measures, but also it depends on the way of collecting benchmarking data. Therefore, generic benchmarking data collection processes were defined in order to be applied in an organization to guarantee accurate and efficient benchmarking data repository.

Meanwhile, collecting benchmarking data is an extensive and difficult task which needs large effort. In organizations without defined benchmarking measures and data collection procedures it is really hard and time consuming task to collect projects’ historical data. So, in order to facilitate this task, in this study after defining benchmarking measures and data collection processes, a data collection tool was implemented accordingly to support benchmarking data collection.

Two case studies were conducted in this research, the first case study was exploratory case study, and the second one was for validation of benchmarking methodology. In the first step of the exploratory case study, effort drivers and important projects attributes which had to be collected in data repositories in an organization were explored. Also, an extended comparison study of data repositories from effort estimation perspective was conducted and important benchmarking measures were identified. Then feasibility of these identified measures was investigated in a software organization by inspecting 11 projects data and then benchmarking measures were refined as a result. We observed large variances (from 1.47 Person-hours/ FP to 13.66 Person-hours/ FP) in size/ effort ratios of some projects. In some projects the functional similarity rate was high, and by considering reflective functional similarity size (OzanTop O., 2008) of these projects these variances (from 1.42 Person-hours/ FP to 6.6 Person-hours/ FP) was decreased significantly. Also, a project data from another company was collected in order to study quality of data. Three level of data quality (level A, B, and C) were identified considering quality of effort data and the frequency of effort data collection in the organization.

In this study benchmarking data collection processes which were defined by Ozcantop & Demirors (2011) are refined. Subsequently, a benchmarking data collection tool was implemented and integrated on Cubit toolset by considering these refined benchmarking measures and benchmarking data collection processes. This tool supports all benchmarking data collection processes steps and enables users to collect projects' data according to defined procedure. Using this tool decreased collection time and effort consumed for data collection, and also it partially validated the benchmarking data, and it increased accuracy of benchmarking data in the data repository. Without using benchmarking data collection tool, data collection task was difficult and time consuming because it had to be done by interview with data submitter. Since benchmarking measures and data collection processes were not identified clearly, in order to get accurate data from data submitter, data collector is supposed to spend an amount of time to give necessary information to data submitter. Since Cubit provides users the feature of recording details of projects functional size measurement, it is possible to calculate reflective functional similarity size of the projects in a reliable and easier way.

Cubit benchmarking tool is utilized for collecting internal benchmarking data in organizations. Our previous study showed that effort estimation based on internal benchmarking data repositories produces more accurate results than external benchmarking data repositories (OzcanTop et.al, 2011). So, we implemented internal benchmarking data collection tool. However, as all organizations uses common data base through web application, Cubit also has the potential to collect data for external data repository.

In the second case study the proposed benchmarking methodology was validated. In this case study 40 projects data were collected from a middle size software organization by using Cubit benchmarking tool. Projects data were examined in detail and we observed that fill in ratio for project type, industry type, functional domain type, tool usage, experience of team members, stability of team, all attributes in product attribute categories, effort attributes of requirements, design, coding and testing activities, and details of size measurement and reflective functional size of projects were 100%. Since in this organization we collected data of finished projects, we couldn’t collect remaining benchmarking attributes. But if the benchmarking data collection processes were pursued then we would be able to collect these project attributes.

Moreover, effort/size ratios for every project were also calculated for total effort, development effort, and each of software development activities. Since projects belonged to three different functional domain types, and projects in each of these functional domain types were developed under same situations, we expected productivity ratio to be in the same range for all projects in the same functional domain type. But there were some outliers and productivity ratio variances revealed some projects characteristics which can be the reasons for this unusual behavior of effort/size ratios. First, there was some reuse rate in the terms of functional similarity in some of collected projects data. Additionally, some of the projects include very complex algorithms which cannot be measured by using COSMIC measurement method, and they were ignored during measurement. Since source code of these projects were not available we couldn't reach any standard defined complexity measure of these projects, therefore we classified algorithm complexity level of these projects into three levels of Basic Algorithms, Medium Complex Algorithms, and Very Complex Algorithms by interviewing to data submitter. It was observed that most of the projects with outlier effort/size ratio were classified in Very Complex Algorithms level. As a discussion it should be mentioned that, algorithm complexity was defined as nominal scale, and classifying algorithms based on defined algorithm complexity may be subjective.

In some other projects which had large total effort/size ratio, the software were designed for control function of a new hardware, and unfamiliarity of the hardware causes extra effort load for the project (especially for testing activities). Besides, in this organization a special standard was applied for some projects which lead to produce extra testing activities for these projects. Consequently the total effort for these projects were increased and caused the unusual behavior of effort/size ratio.

After these observations, in order to evaluate collected data, effort estimation models were constructed using simple regression models and considering MMRE and PRED (30) values. In these models total effort was dependent variable, and size value was independent variable. These estimation models were compared to similar models of other data repositories in the literature. Although both MMRE and PRED values for all effort estimation models were not in acceptable boundaries, we observed improvements. In order to consider an effort estimation model as an accurate prediction, PRED (30) value should be higher than 60% (Tunalilar, S., 2011). PRED (30) value of our models for total effort estimation increased to 22.5% and by considering functional similarity it increased to 37%.

Subsequently, we created effort estimation models by considering development effort, and effort for each activity in software development lifecycle as dependent variable, and size effort as independent variables. Results showed that considering reflective functional similarity and functional domain type improved the accuracy of benchmarking data in the data repositories, and more accurate effort estimation models were constructed in this way. The prediction level parameter PRED (30) increased to 45.45% for project data with Simple Control System (SCS) Functional domain type, 33.33% for project data with Complex Control System (CCS) Functional domain type, and 41.17% for project data with Complex Data Driven Control System (CDDCS) Functional domain type for total effort estimation models. In addition PRED (30) value increased to 55.55% for SCS projects, 33.33% for CCS projects, and 52.94% for CDDCS project for development effort estimation models. Also, it is observed that estimation models for development effort produced more accurate data in comparison to estimation models for total effort data.

We also created effort estimation models with multiple regression models by considering effort data as dependent variable, and number of BFC of COSMIC method (Enter, Exit, Read, and Write) as independent variables. We also take into account functional similarity, and classification of projects based on their functional domain type. The results show that, when we collect projects size data in BFC level and projects' effort data in activity level we conclude in better estimation. PRED (30) values for SCS projects increased to 72.72 % for requirements activities, 81.81% for coding activities, and 81.81% for testing activities. For CCS projects these values were 72.72%, 45.45%, and 50% respectively. Also, it should be reminded that functional similarity and functional domain type were also accounted.

As contribution of this study, it was the first time that all proposed benchmarking improvements of benchmarking measure, benchmarking data collection processes, and tool support were utilized together to improve quality of benchmarking data repository. Also, reflective functional size was used in previous studies for effort estimation research but it was the first time it was collected for the benchmarking purpose in benchmarking data repositories. In addition, using algorithm complexity suggested as an improvement to benchmarking attributes. The results show that, some effort records are not classified under software development effort like ideal effort, standard application effort, and also documentation effort which increase the total effort of projects. So, these efforts should be considered as an extension of collected effort.

Another contribution of our study is that the benchmarking tool can be tailored for an organization, and it can benefit organizations for constructing an internal software benchmarking repository.

5.2. Future Work

In our study we observed improvements in the quality of benchmarking data repository, but there are still improvement opportunities that can be explored.

The study conducted considering projects data of three software organizations, and it can be investigated in other organizations in order to achieve more improvements for benchmarking data repositories. In our study we collected data by using interviews, and we assumed submitted data is reliable. Violation of this assumption can reduce validity of our study. As future work automated effort data collector and other measure collectors can be integrated to Cubit to improve the accuracy of collected data. Also, the impact of missing data on the quality of the data in our dataset can be investigated as a future work.

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APPENDIX

EPC Diagrams for Benchmarking Data Collection Processes

1. Infrastructure Definition Process

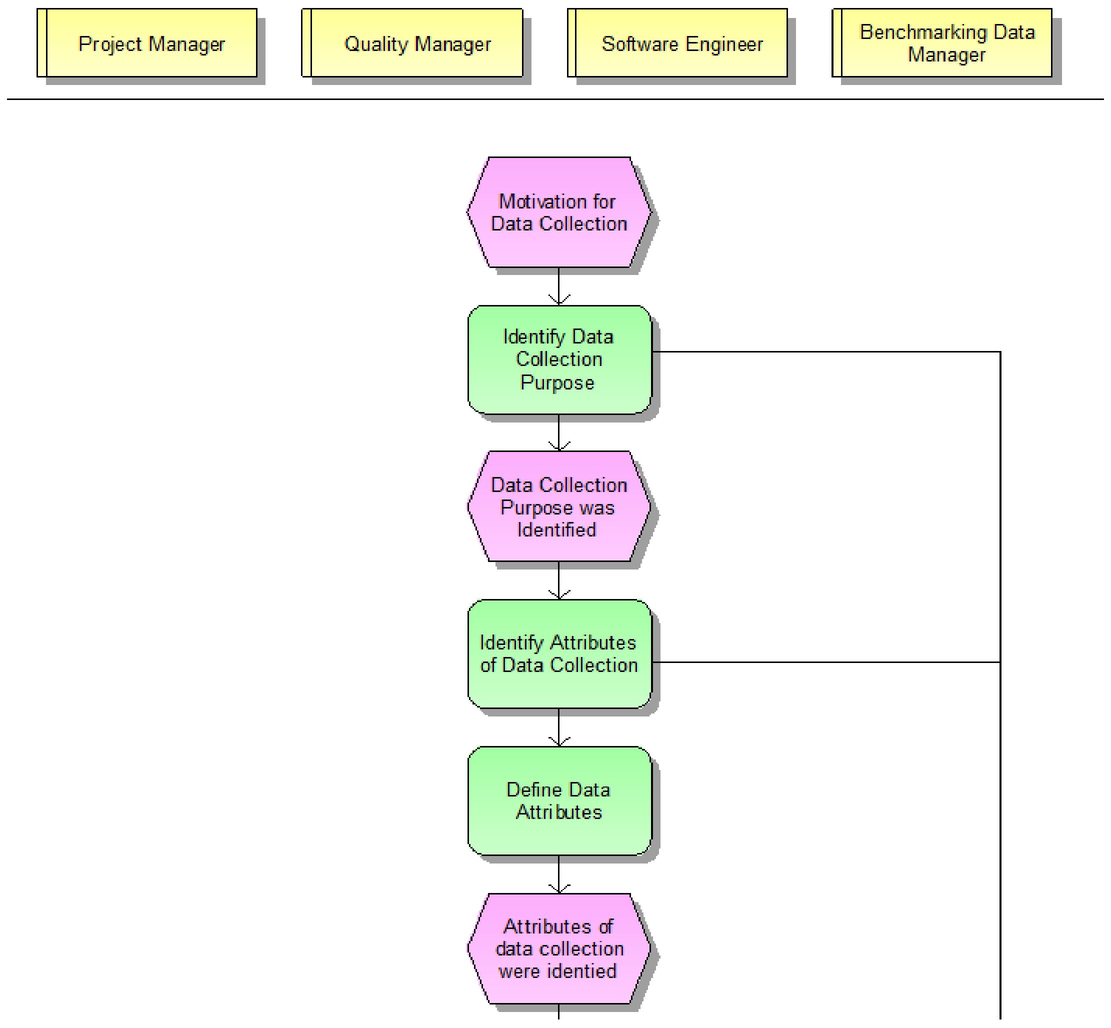
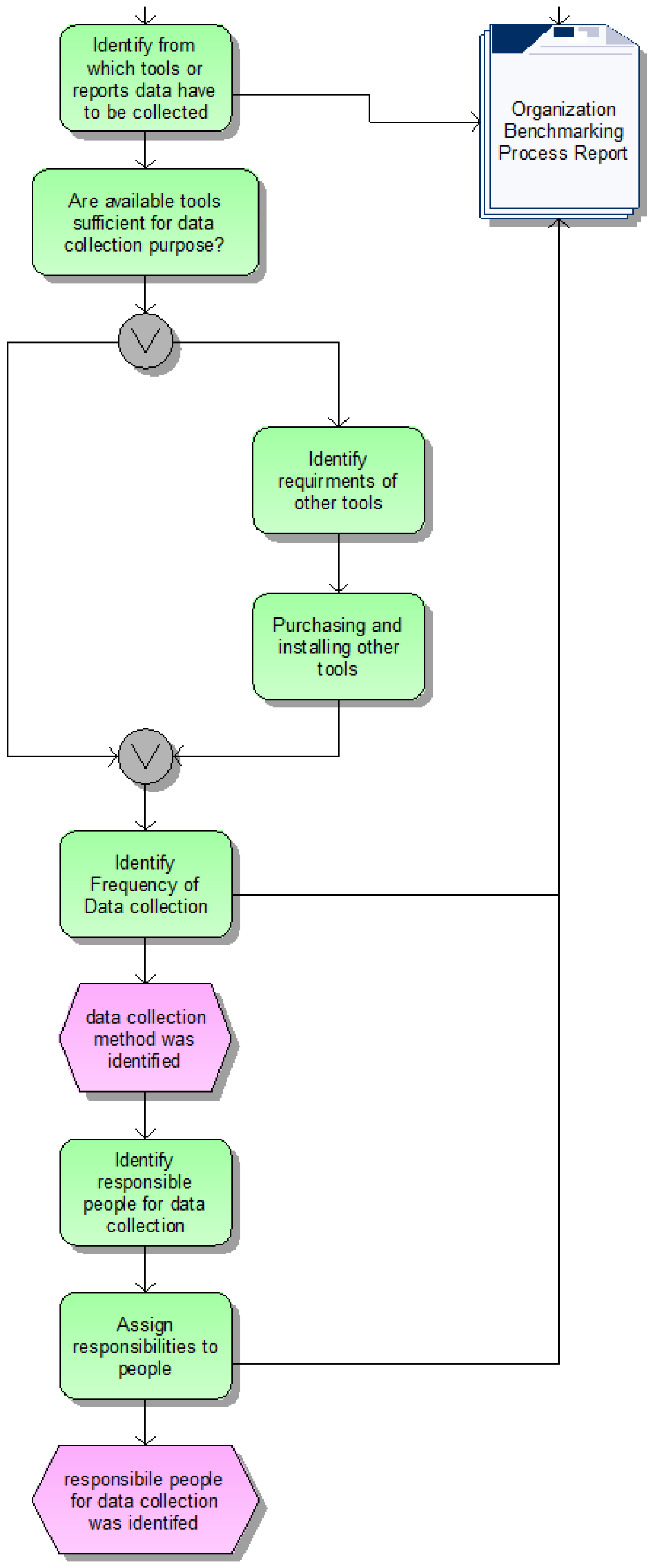

Project Manager
Quality Manager
Software Engineer
Benchmarking Data Manager
Motivation for Data Collection
Identify Data Collection Purpose
Data Collection Purpose was Identified
Identify Attributes of Data Collection
Define Data Attributes
Attributes of data collection were identied

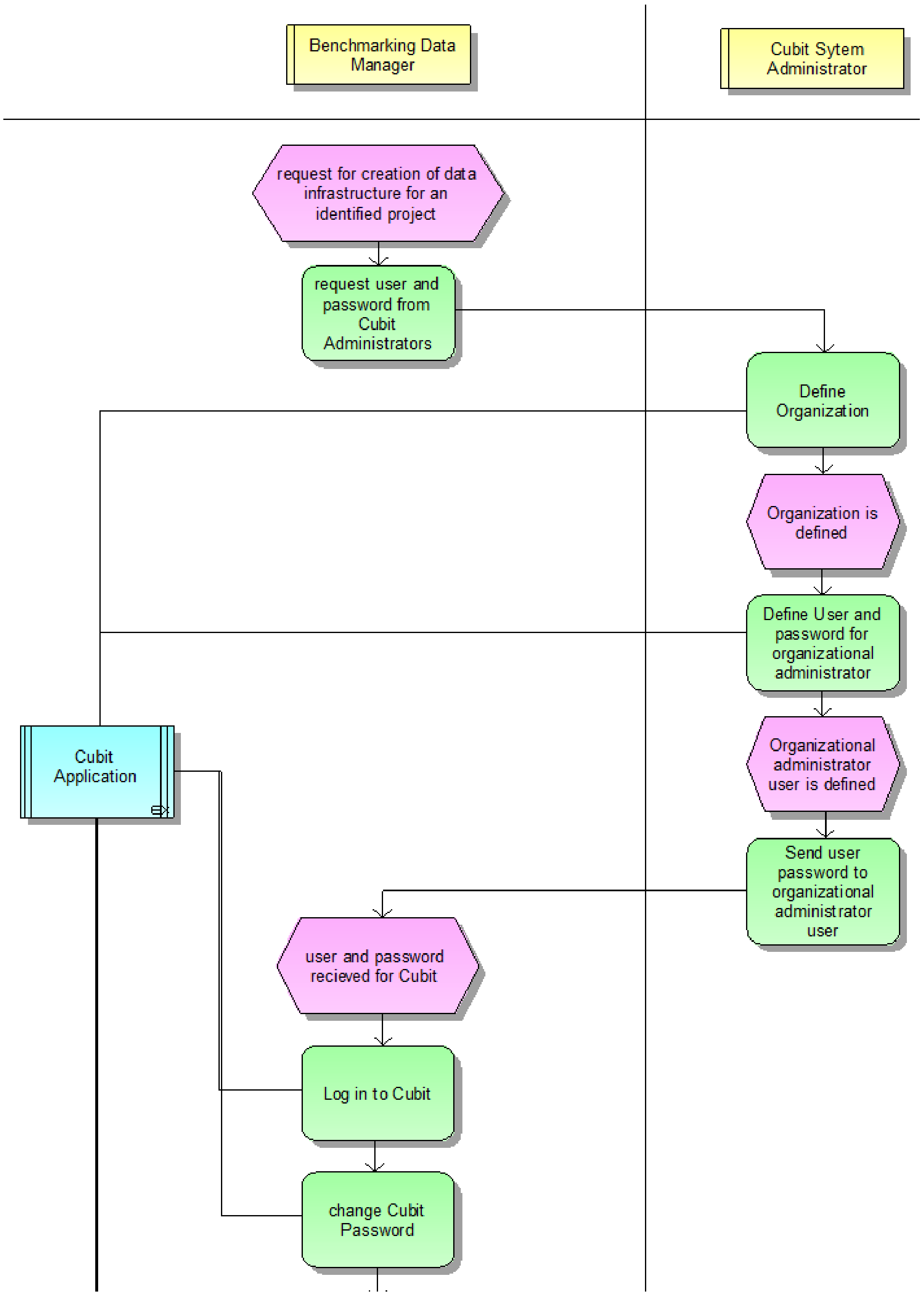
Figure 10: Infrastructure Definition Process



Identify from which tools or reports data have to be collected
Organization Benchmarking Process Report
Are available tools sufficient for data collection purpose?
Identify requirments of other tools
Purchasing and installing other tools
Identify Frequency of Data collection
data collection method was identified
Identify responsible people for data collection
Assign responsibilities to people
responsibile people for data collection was identifed

Figure 10: Infrastructure Definition Process (Continued)

2. Cubit Infrastructure Definition Process



Benchmarking Data Manager
Cubit Sytem Administrator
request for creation of data infrastructure for an identified project
request user and password from Cubit Administrators
Define Organization
Organization is defined
Define User and password for organizational administrator
Organizational administrator user is defined
Send user password to organizational administrator user
Cubit Application
user and password recieved for Cubit
Log in to Cubit
change Cubit Password

Figure 11: Cubit Infrastructure Definition Process

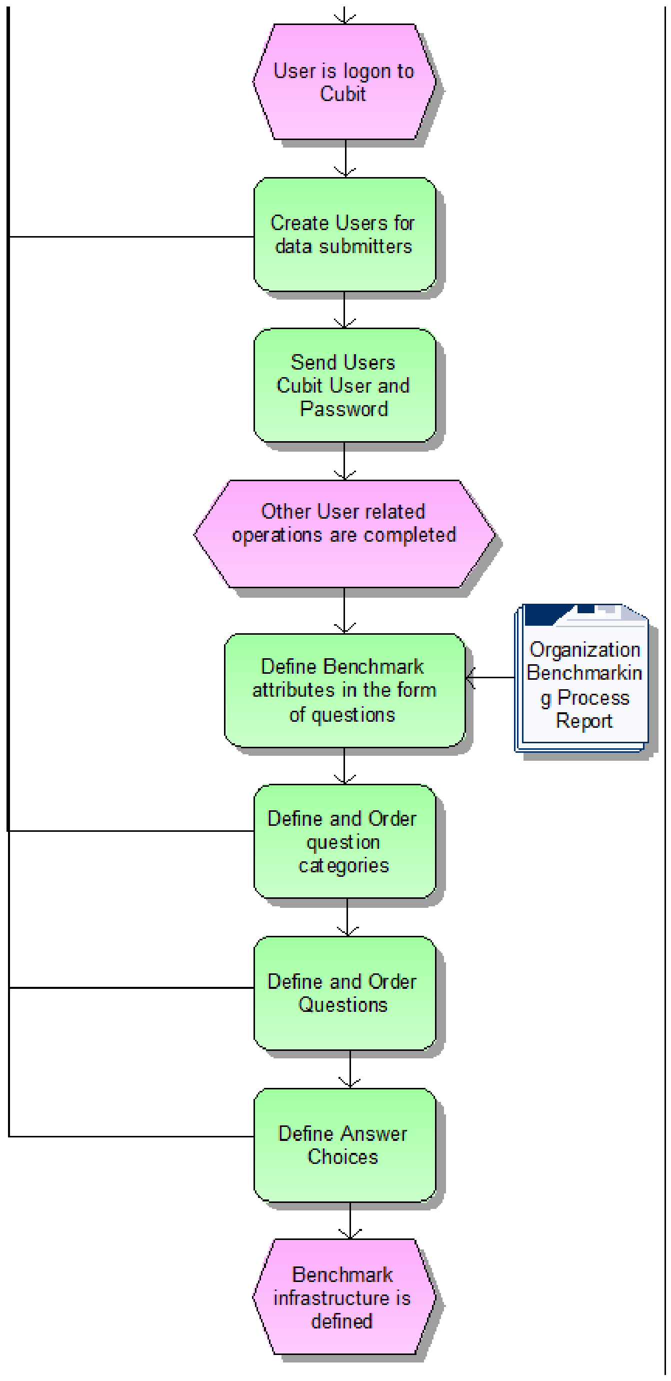

User is logon to Cubit
Create Users for data submitters
Send Users Cubit User and Password
Other User related operations are completed
Define Benchmark attributes in the form of questions
Organization Benchmarking Process Report
Define and Order question categories
Define and Order Questions
Define Answer Choices
Benchmark infrastructure is defined

Figure 11: Cubit Infrastructure Definition Process (Continued)

3. Data Collection Process

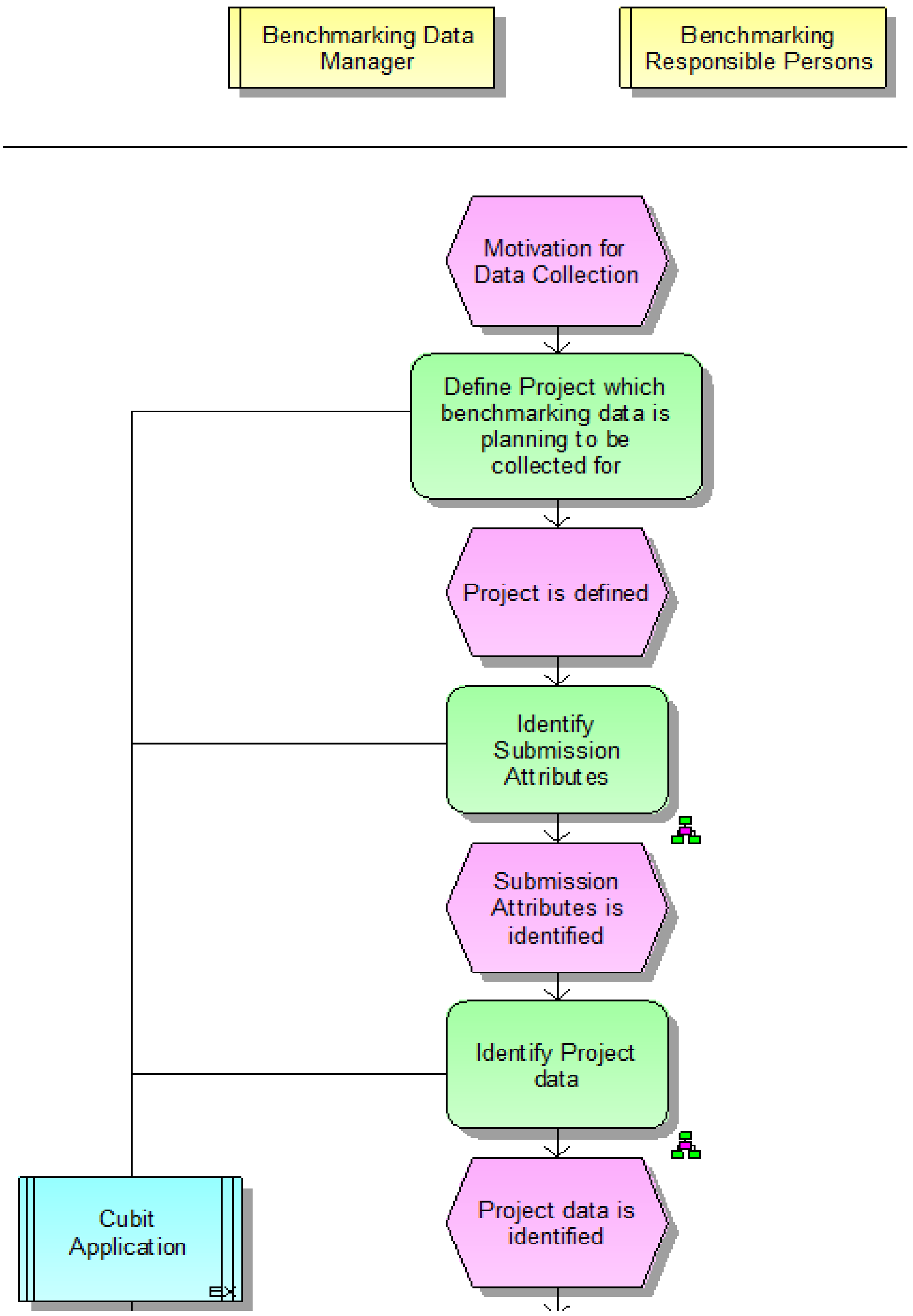

Benchmarking Data Manager
Benchmarking Responsible Persons
Motivation for Data Collection
Define Project which benchmarking data is planning to be collected for
Project is defined
Identify Submission Attributes
Submission Attributes is identified
Identify Project data
Project data is identified
Cubit Application

Figure 12: Data Collection Process

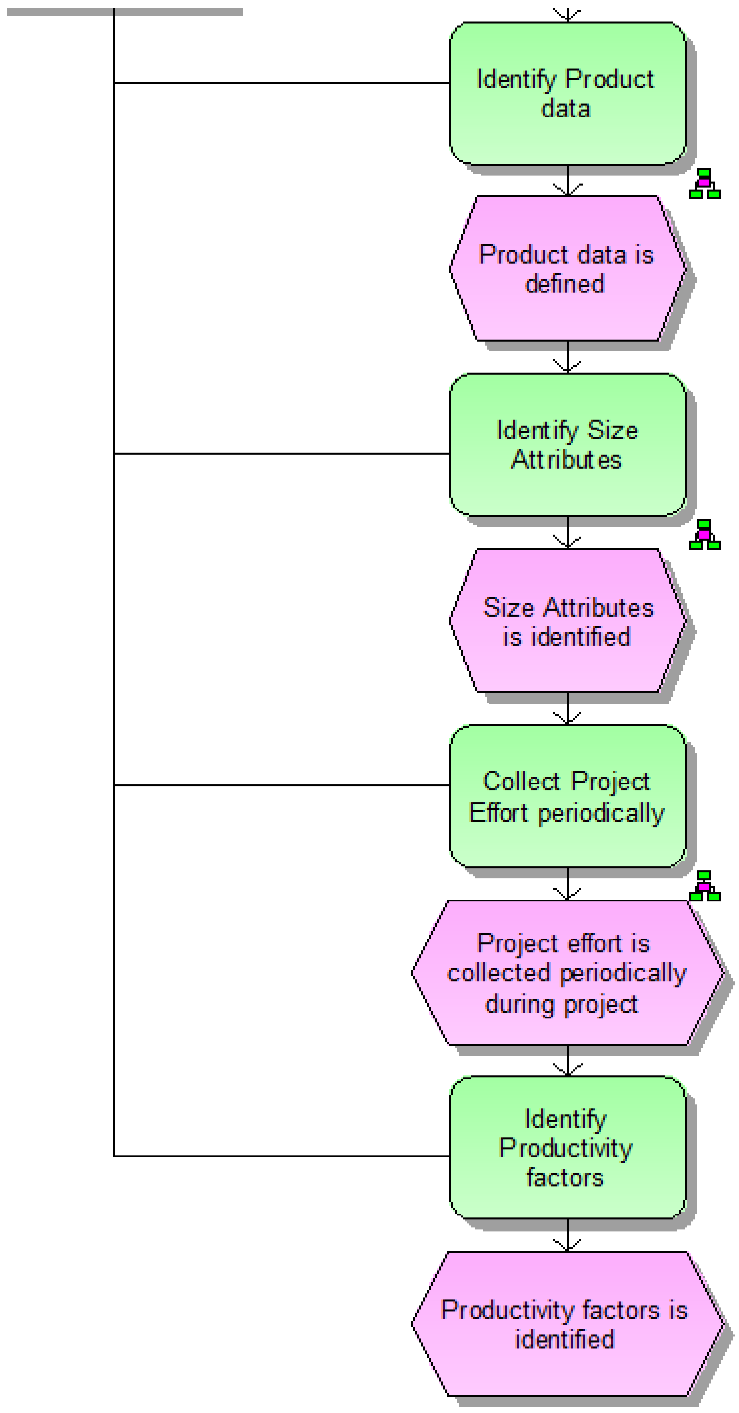
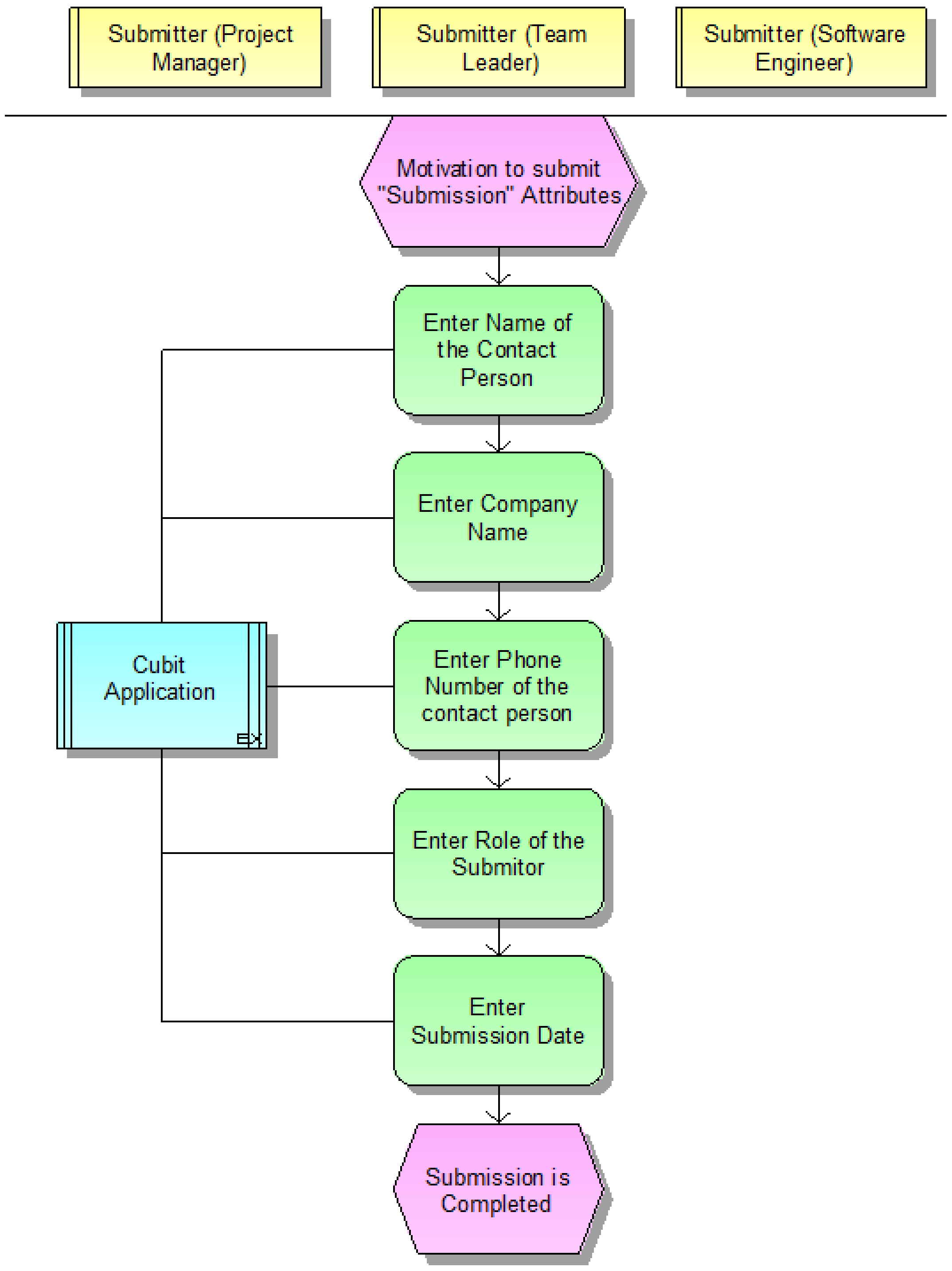

Identify Product data
Product data is defined
Identify Size Attributes
Size Attributes is identified
Collect Project Effort periodically
Project effort is collected periodically during project
Identify Productivity factors
Productivity factors is identified

Figure 12: Data Collection Process (Continued)

3.1. Submission Attributes Data Collection Process



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit "Submission" Attributes
Enter Name of the Contact Person
Enter Company Name
Cubit Application
Enter Phone Number of the contact person
Enter Role of the Submitor
Enter Submission Date
Submission is Completed

Figure 13: Submission Attributes Data Collection Process

3.2. Project Attributes Data Collection Process

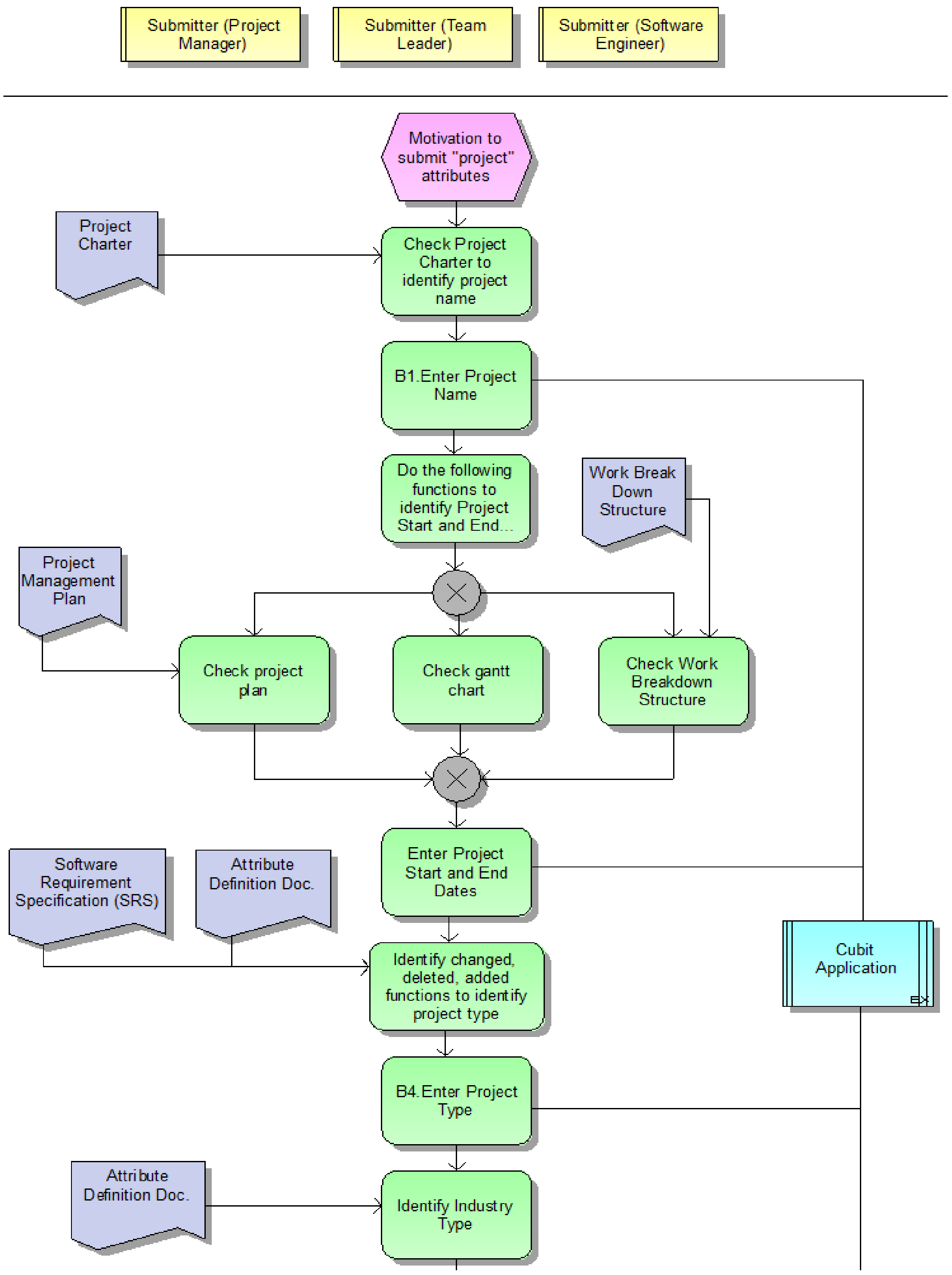
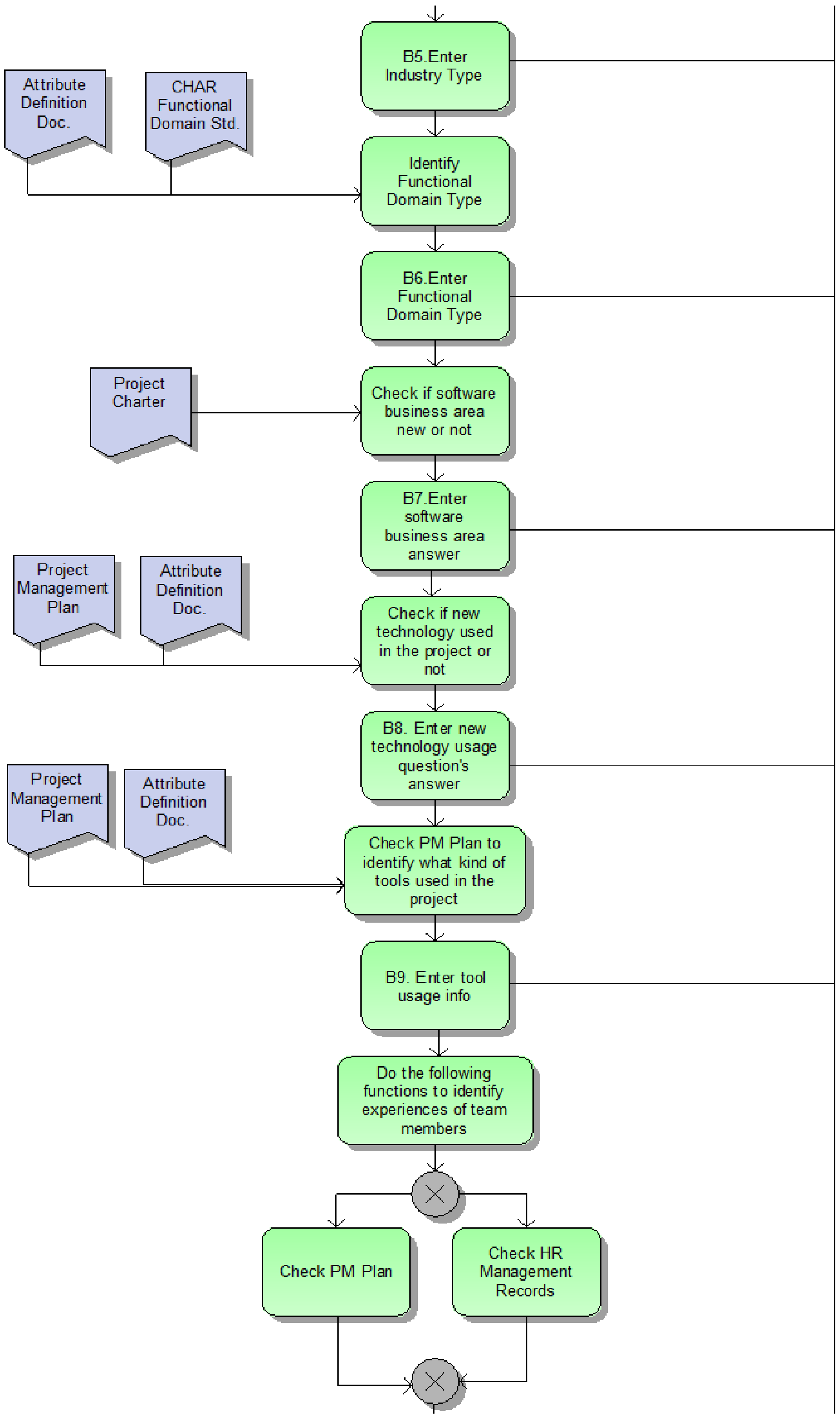

Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit "project" attributes
Project Charter
Check Project Charter to identify project name
B1.Enter Project Name
Do the following functions to identify Project Start and End...
Work Break Down Structure
Project Management Plan
Check project plan
Check gantt chart
Check Work Breakdown Structure
Software Requirement Specification (SRS)
Attribute Definition Doc.
Enter Project Start and End Dates
Cubit Application
Identify changed, deleted, added functions to identify project type
B4.Enter Project Type
Attribute Definition Doc.
Identify Industry Type

Figure 14: Project Attributes Data Collection Process



B5.Enter Industry Type
Attribute Definition Doc.
CHAR Functional Domain Std.
Identify Functional Domain Type
B6.Enter Functional Domain Type
Project Charter
Check if software business area new or not
B7.Enter software business area answer
Project Management Plan
Attribute Definition Doc.
Check if new technology used in the project or not
B8. Enter new technology usage question's answer
Project Management Plan
Attribute Definition Doc.
Check PM Plan to identify what kind of tools used in the project
B9. Enter tool usage info
Do the following functions to identify experiences of team members
Check PM Plan
Check HR Management Records

Figure 14: Project Attributes Data Collection Process (Continued)

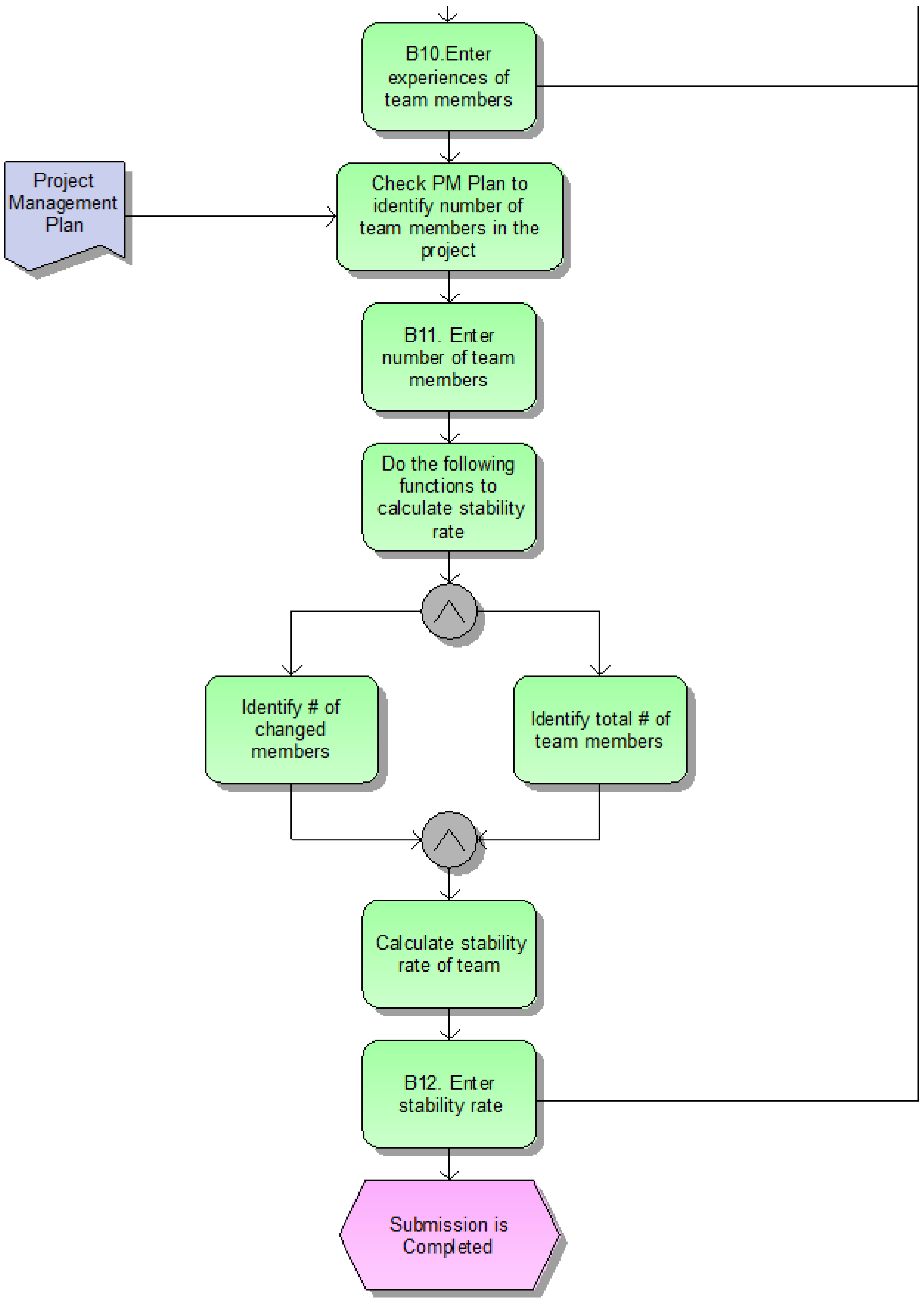

B10.Enter experiences of team members
Project Management Plan
Check PM Plan to identify number of team members in the project
B11. Enter number of team members
Do the following functions to calculate stability rate
Identify # of changed members
Identify total # of team members
Calculate stability rate of team
B12. Enter stability rate
Submission is Completed

Figure 14: Project Attributes Data Collection Process (Continued)

3.3. Product Attributes Data Collection Process

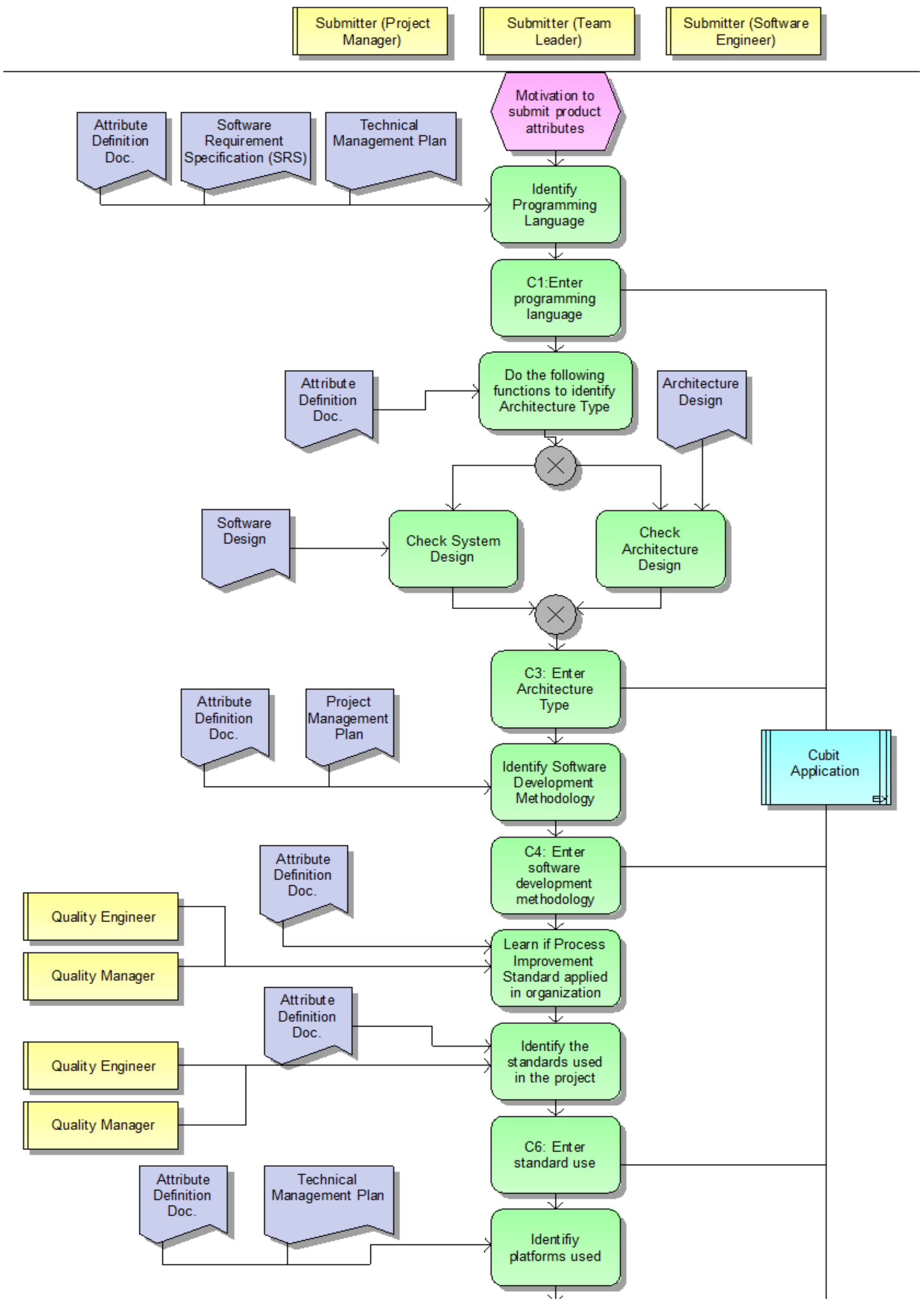

Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit product attributes
Attribute Definition Doc.
Software Requirement Specification (SRS)
Technical Management Plan
Identify Programming Language
C1:Enter programming language
Attribute Definition Doc.
Do the following functions to identify Architecture Type
Architecture Design
Software Design
Check System Design
Check Architecture Design
C3: Enter Architecture Type
Attribute Definition Doc.
Project Management Plan
Cubit Application
Identify Software Development Methodology
C4: Enter software development methodology
Attribute Definition Doc.
Quality Engineer
Quality Manager
Learn if Process Improvement Standard applied in organization
Attribute Definition Doc.
Quality Engineer
Quality Manager
Identify the standards used in the project
C6: Enter standard use
Attribute Definition Doc.
Technical Management Plan
Identifiy platforms used

Figure 15 : Product Attributes Data Collection Process

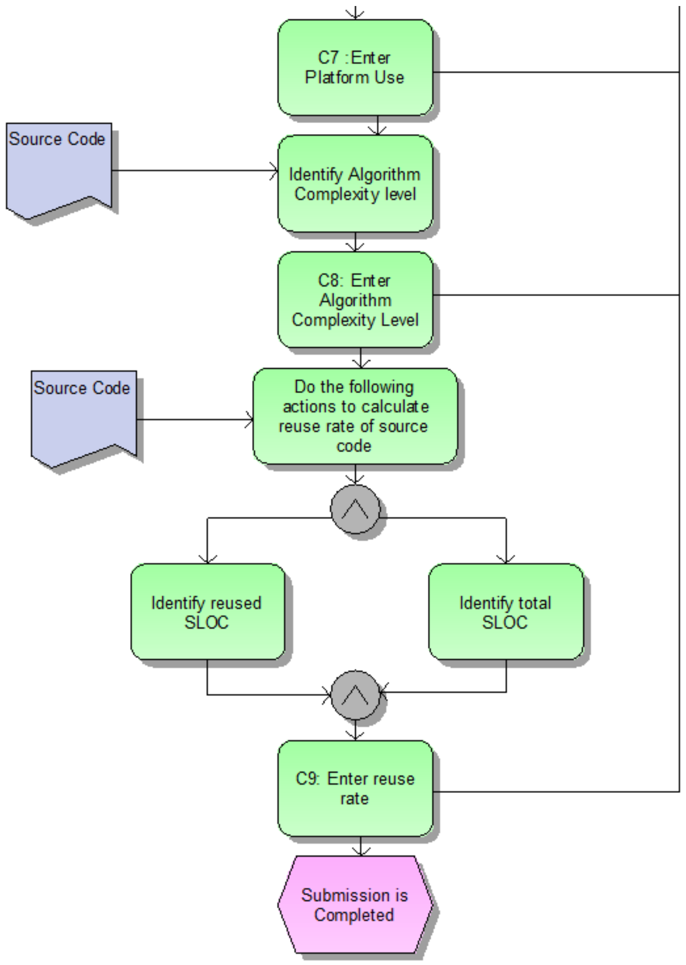

C7 :Enter Platform Use
Source Code
Identify Algorithm Complexity level
C8: Enter Algorithm Complexity Level
Source Code
Do the following actions to calculate reuse rate of source code
Identify reused SLOC
Identify total SLOC
C9: Enter reuse rate
Submission is Completed

Figure 15: Product Attributes Data Collection Process (Continued)

3.4. Software Attributes Data Collection Process size

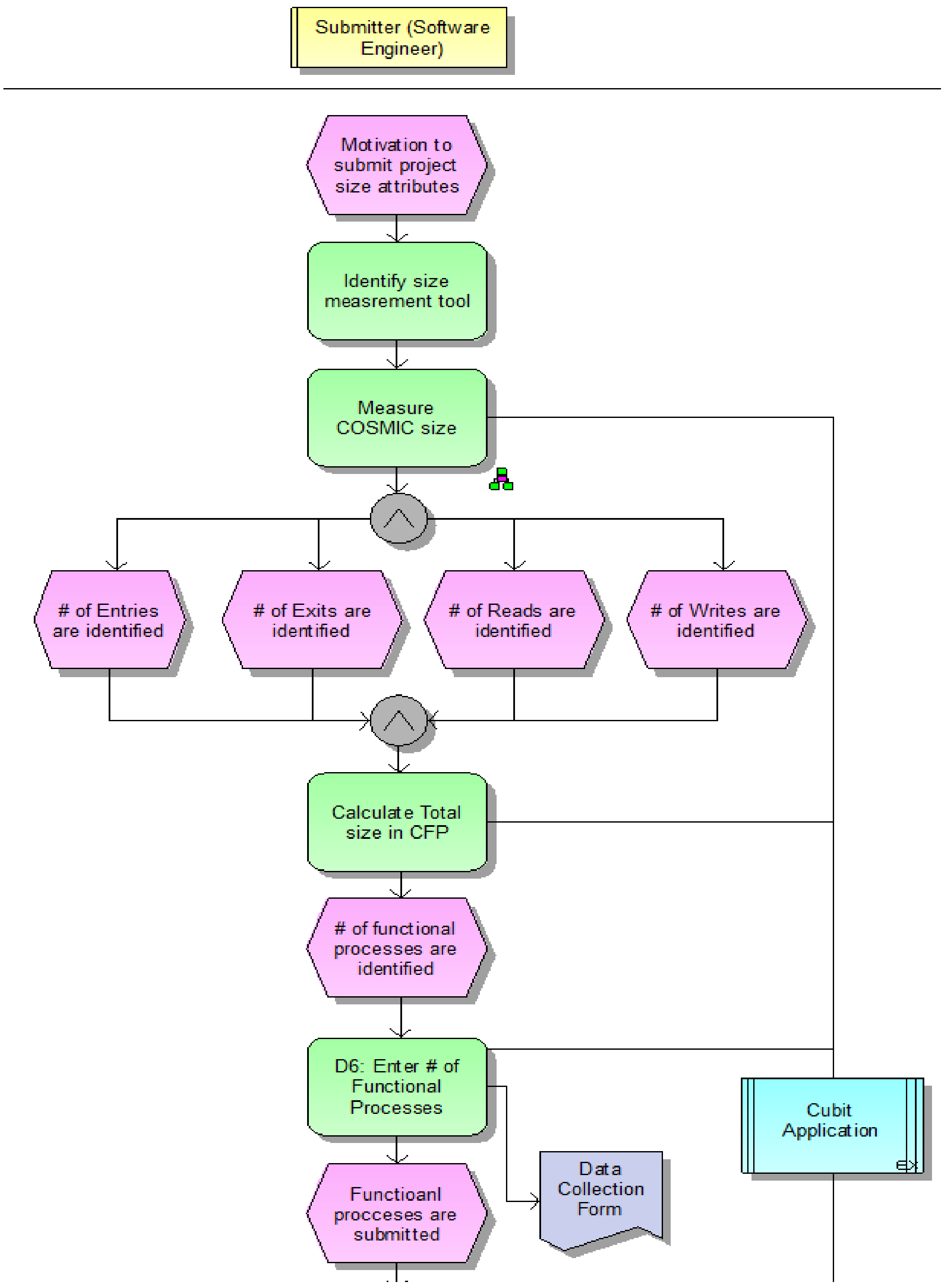
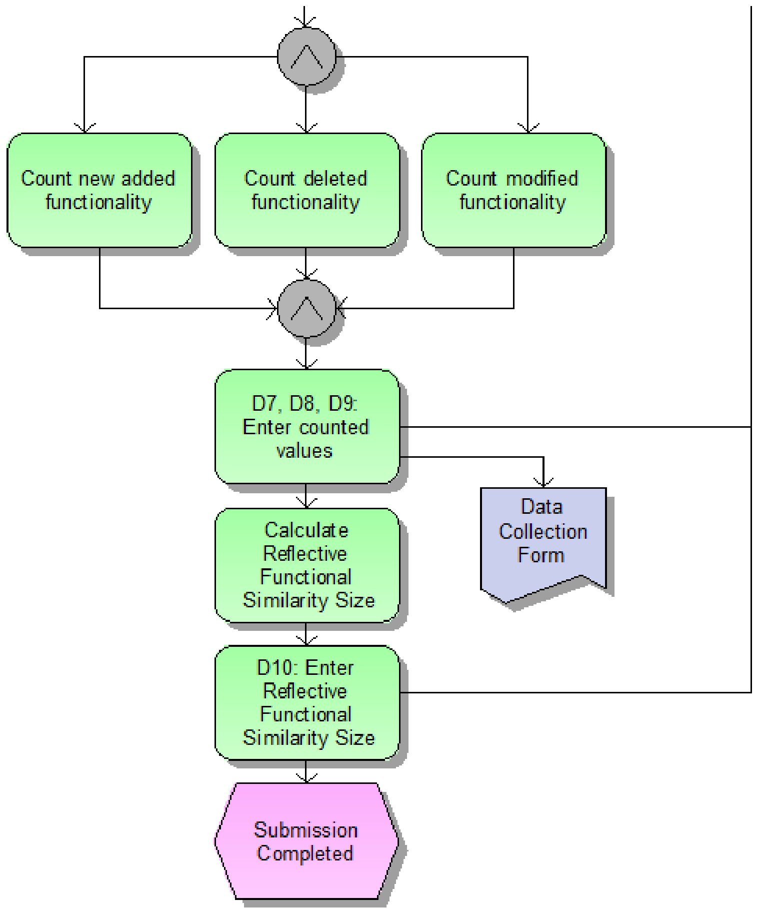

Submitter (Software Engineer)
Motivation to submit project size attributes
Identify size measrement tool
Measure COSMIC size
# of Entries are identified
# of Exits are identified
# of Reads are identified
# of Writes are identified
Calculate Total size in CFP
# of functional processes are identified
D6: Enter # of Functional Processes
Functioanl procceses are submitted
Data Collection Form
Cubit Application

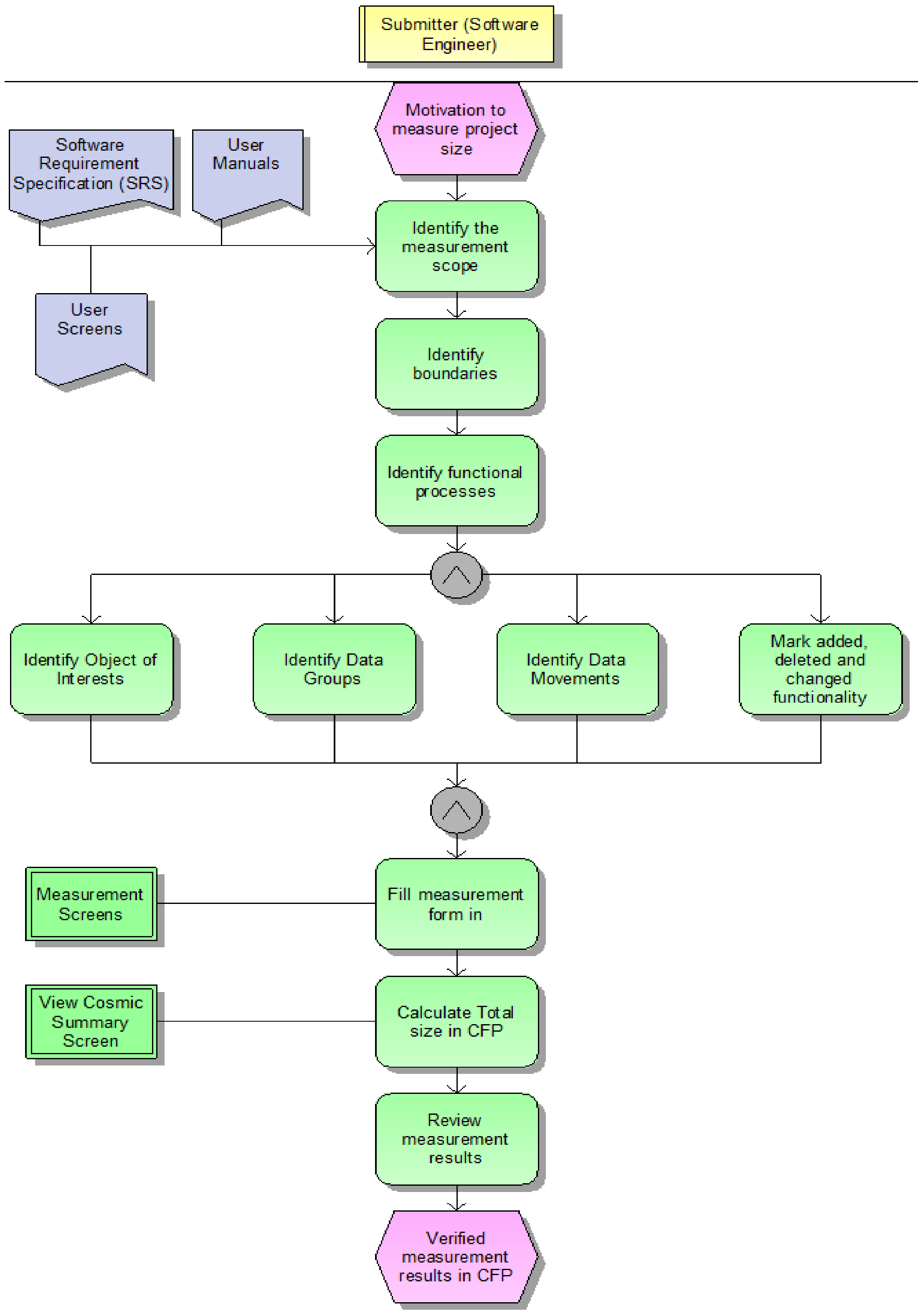
Figure 16: Software Attributes Data Collection Process size



Count new added functionality
Count deleted functionality
Count modified functionality
D7, D8, D9: Enter counted values
Data Collection Form
Calculate Reflective Functional Similarity Size
D10: Enter Reflective Functional Similarity Size
Submission Completed

Figure 16: Software Attributes Data Collection Process size (Continued)

3.4.1. Measure COSMIC size



Submitter (Software Engineer)
Motivation to measure project size
Software Requirement Specification (SRS)
User Manuals
User Screens
Identify the measurement scope
Identify boundaries
Identify functional processes
Identify Object of Interests
Identify Data Groups
Identify Data Movements
Mark added, deleted and changed functionality
Measurement Screens
Fill measurement form in
View Cosmic Summary Screen
Calculate Total size in CFP
Review measurement results
Verified measurement results in CFP

Figure 17: Measure COSMIC size

4. Effort Attributes Data Collection Process

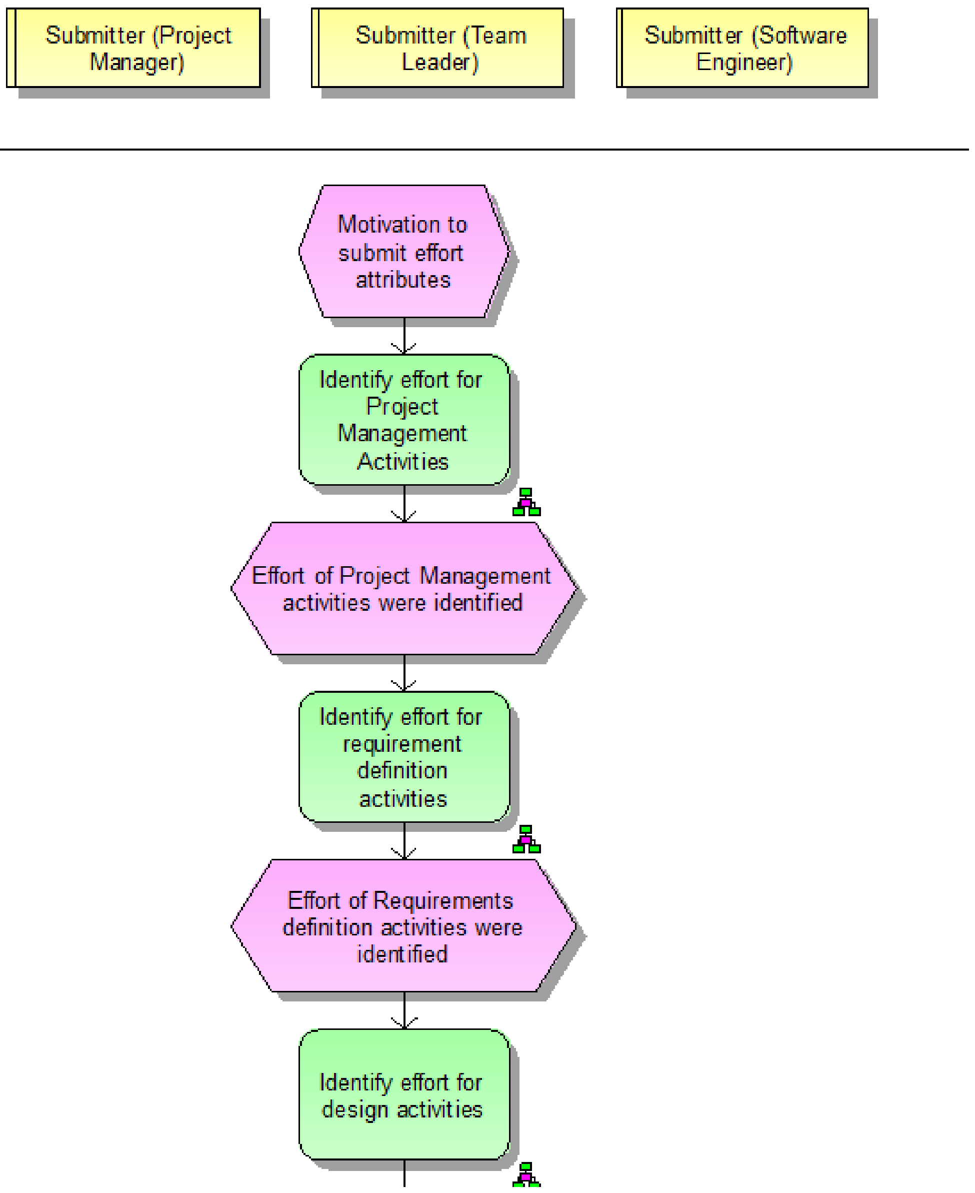

Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit effort attributes
Identify effort for Project Management Activities
Effort of Project Management activities were identified
Identify effort for requirement definition activities
Effort of Requirements definition activities were identified
Identify effort for design activities

Figure 18 : Effort Attributes Data Collection Process

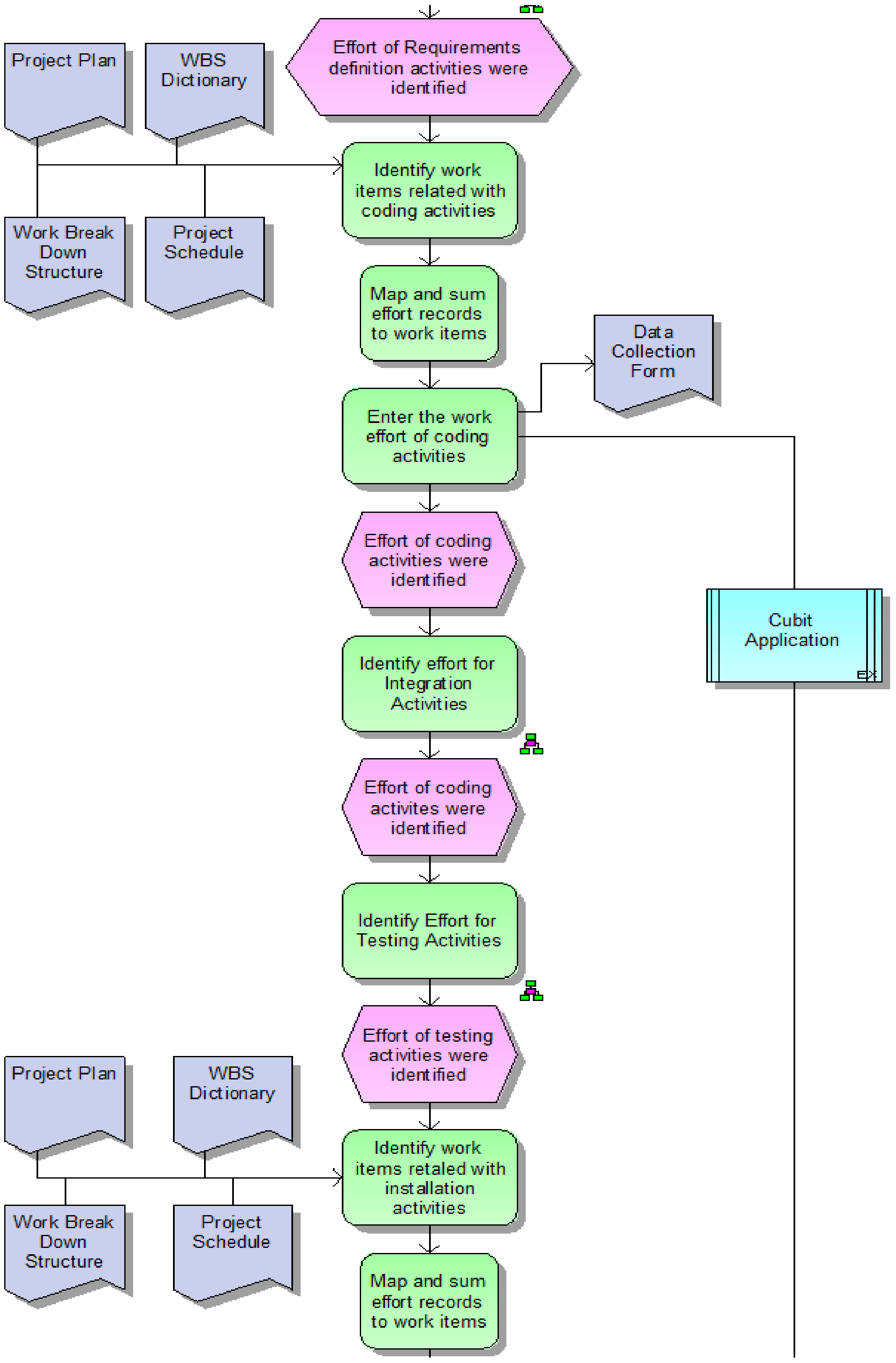
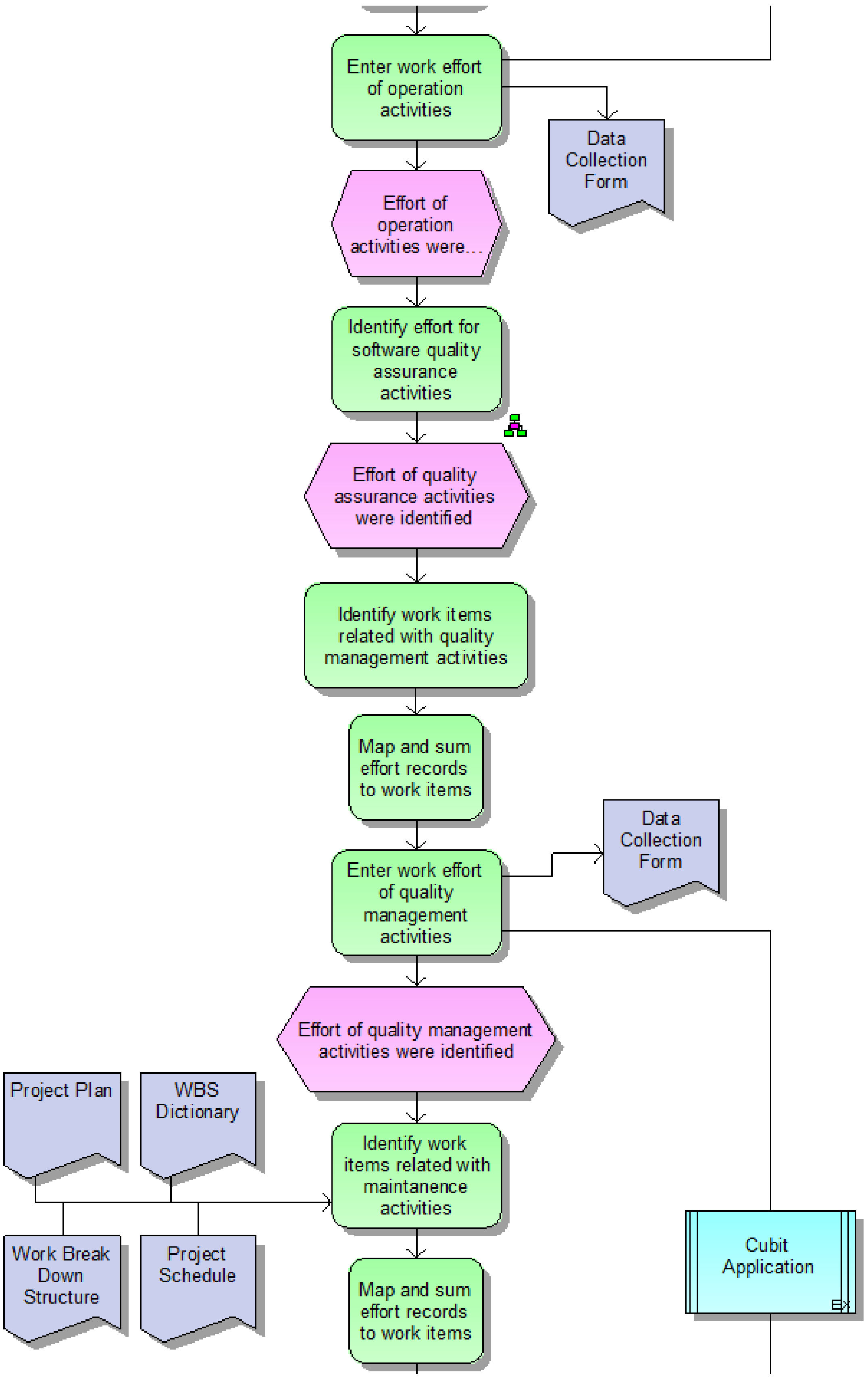
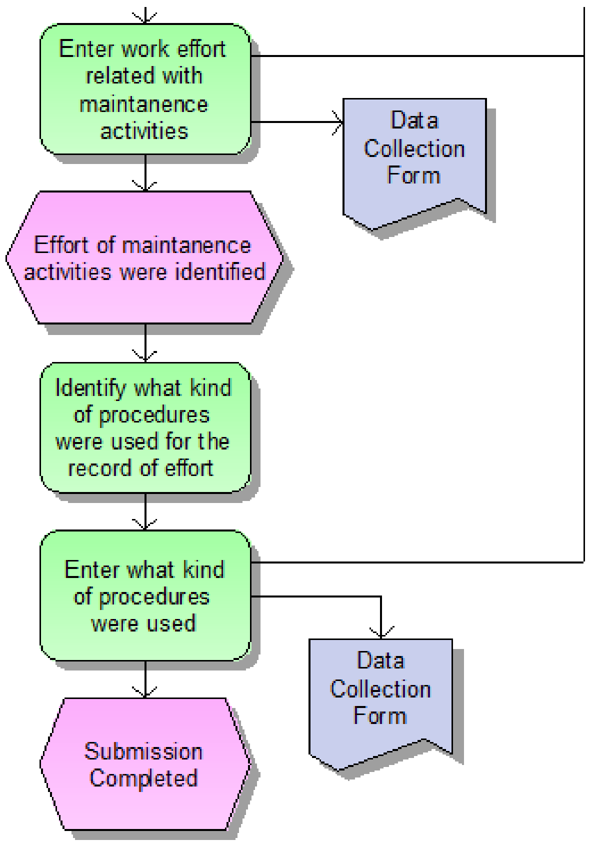

Effort of Requirements definition activities were identified
Project Plan
WBS Dictionary
Identify work items related with coding activities
Work Break Down Structure
Project Schedule
Map and sum effort records to work items
Data Collection Form
Enter the work effort of coding activities
Effort of coding activities were identified
Cubit Application
Identify effort for Integration Activities
Effort of coding activites were identified
Identify Effort for Testing Activities
Effort of testing activities were identified
Project Plan
WBS Dictionary
Identify work items retaled with installation activities
Work Break Down Structure
Project Schedule
Map and sum effort records to work items

Figure 18: Effort Attributes Data Collection Process (Continued)



Enter work effort of operation activities
Data Collection Form
Effort of operation activities were...
Identify effort for software quality assurance activities
Effort of quality assurance activities were identified
Identify work items related with quality management activities
Map and sum effort records to work items
Data Collection Form
Enter work effort of quality management activities
Effort of quality management activities were identified
Project Plan
WBS Dictionary
Identify work items related with maintanence activities
Work Break Down Structure
Project Schedule
Map and sum effort records to work items
Cubit Application

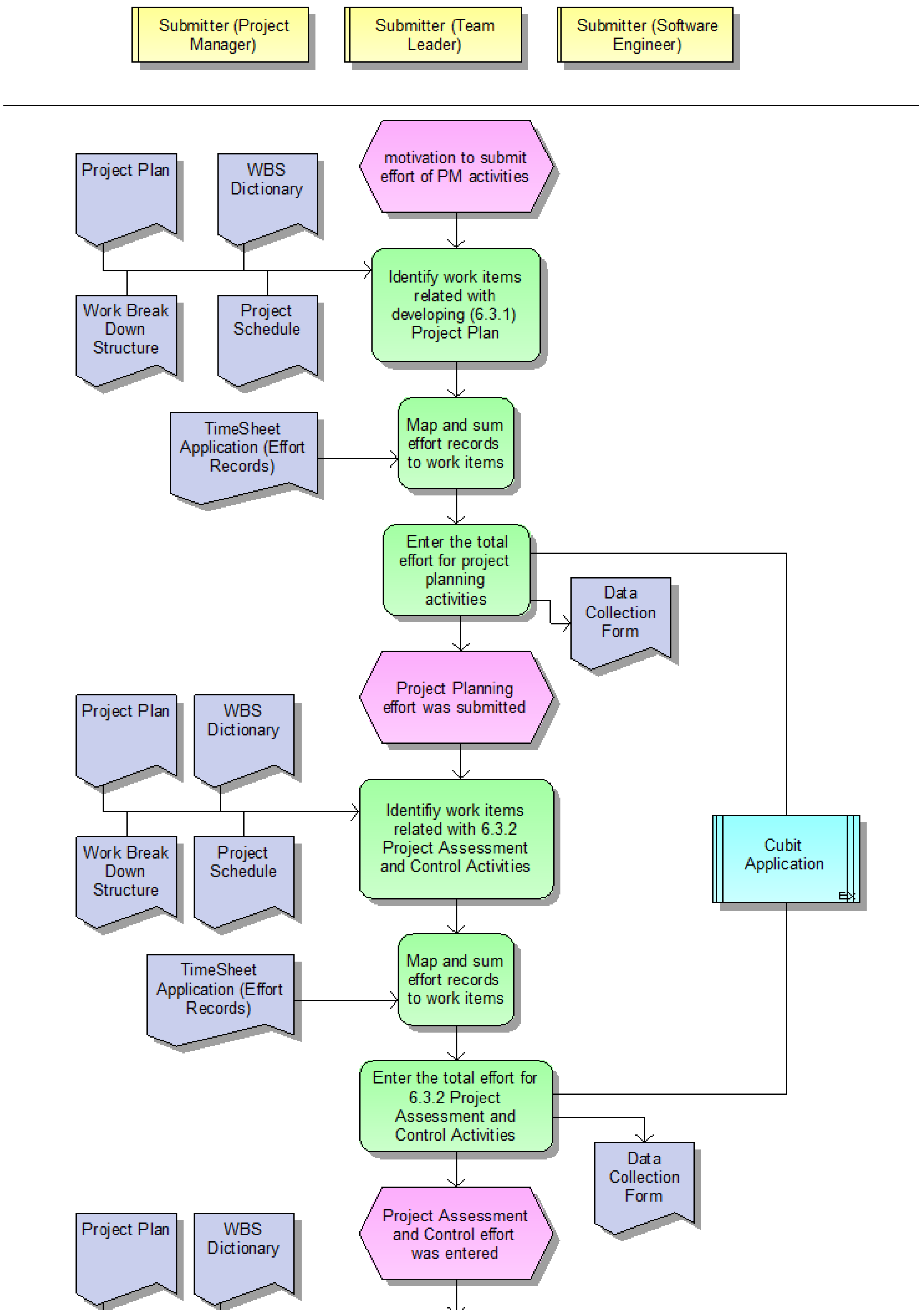
Figure 18: Effort Attributes Data Collection Process (Continued)



Enter work effort related with maintanence activities
Data Collection Form
Effort of maintanence activities were identified
Identify what kind of procedures were used for the record of effort
Enter what kind of procedures were used
Data Collection Form
Submission Completed

Figure 18: Effort Attributes Data Collection Process (Continued)

4.1. Data Collection Process for Project Management Effort Data



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Project Plan
WBS Dictionary
motivation to submit effort of PM activities
Work Break Down Structure
Project Schedule
Identify work items related with developing (6.3.1) Project Plan
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Enter the total effort for project planning activities
Data Collection Form
Project Planning effort was submitted
Project Plan
WBS Dictionary
Identifiy work items related with 6.3.2 Project Assessment and Control Activities
Cubit Application
Work Break Down Structure
Project Schedule
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Enter the total effort for 6.3.2 Project Assessment and Control Activities
Data Collection Form
Project Assessment and Control effort was entered
Project Plan
WBS Dictionary

Figure 19: Data Collection Process for Project Management Effort Data

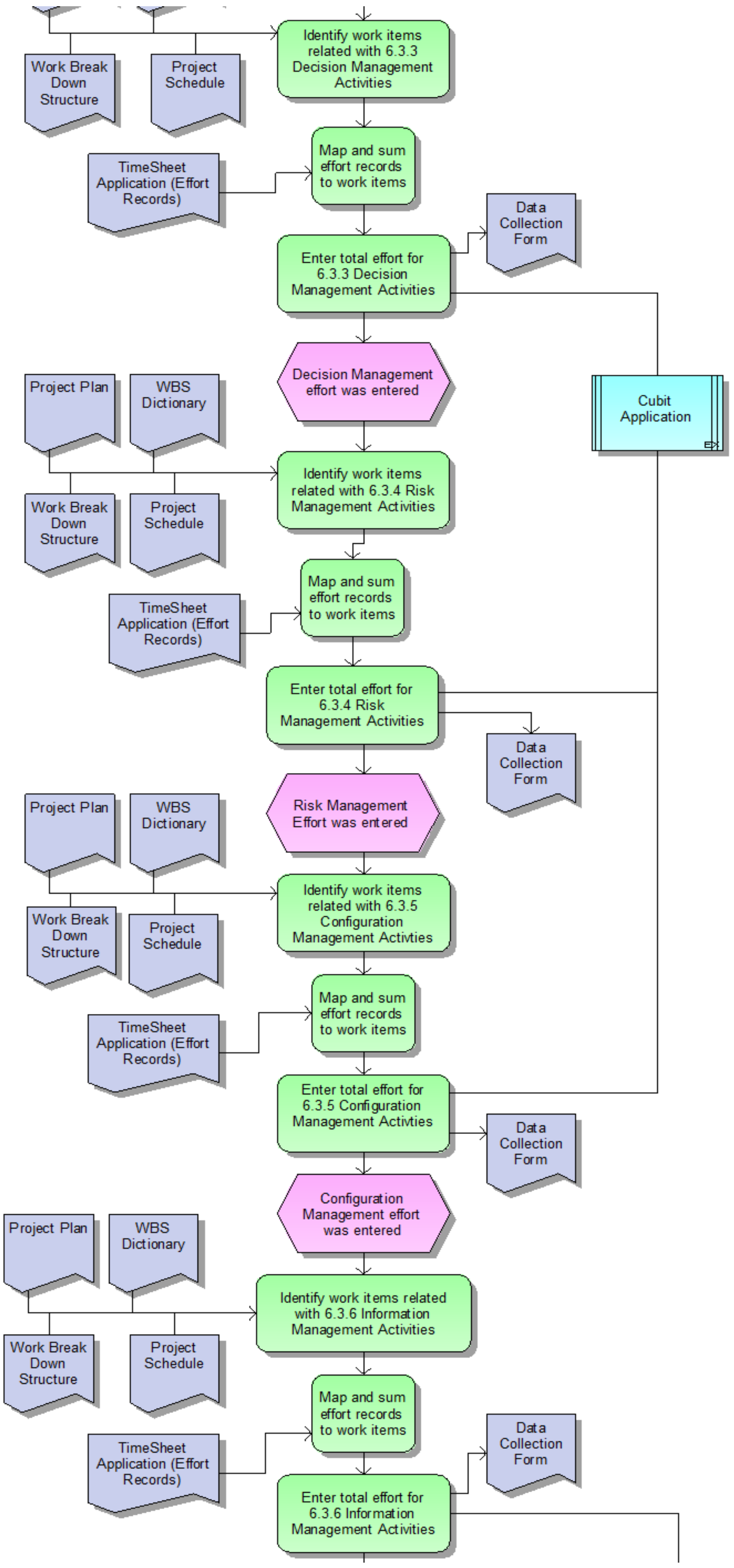
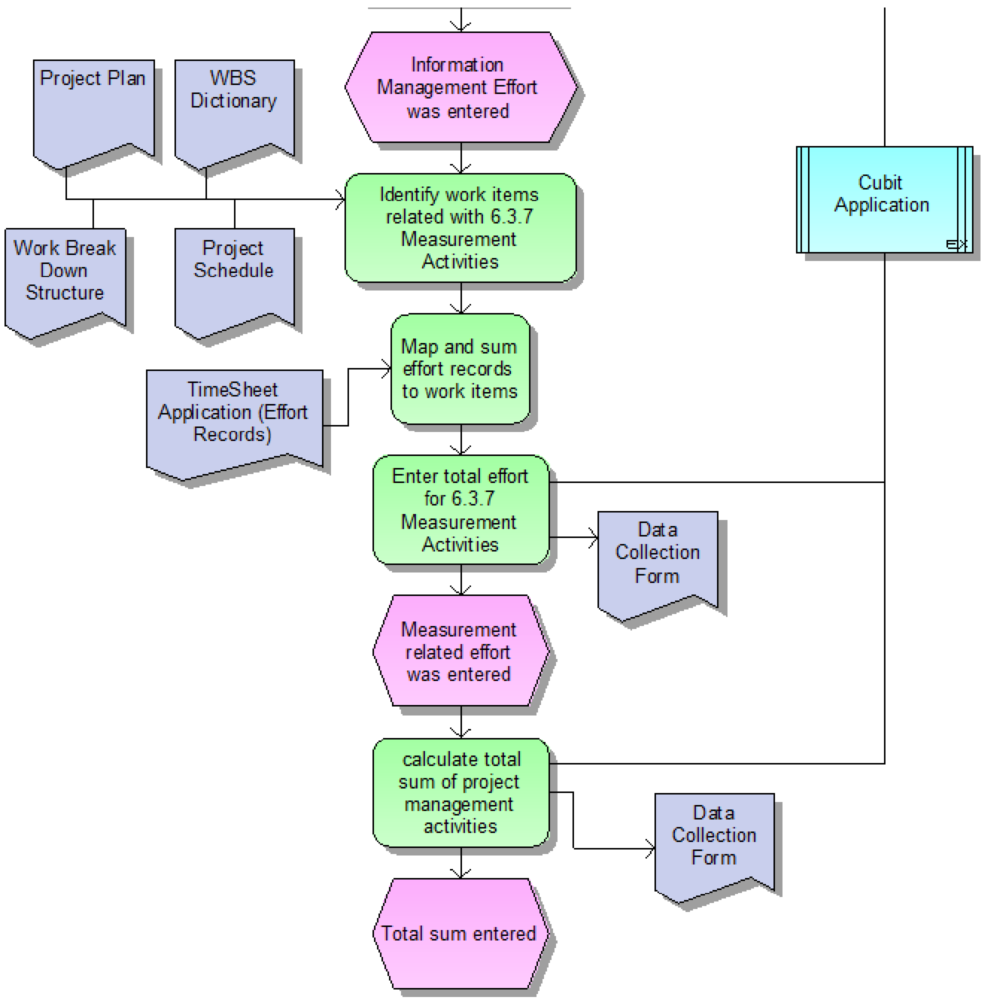

Work Break Down Structure
Project Schedule
Identify work items related with 6.3.3 Decision Management Activities
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Data Collection Form
Enter total effort for 6.3.3 Decision Management Activities
Decision Management effort was entered
Cubit Application
Project Plan
WBS Dictionary
Work Break Down Structure
Project Schedule
Identify work items related with 6.3.4 Risk Management Activities
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Enter total effort for 6.3.4 Risk Management Activities
Data Collection Form
Risk Management Effort was entered
Project Plan
WBS Dictionary
Work Break Down Structure
Project Schedule
Identify work items related with 6.3.5 Configuration Management Activties
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Enter total effort for 6.3.5 Configuration Management Activties
Data Collection Form
Configuration Management effort was entered
Project Plan
WBS Dictionary
Work Break Down Structure
Project Schedule
Identify work items related with 6.3.6 Information Management Activities
TimeSheet Application (Effort Records)
Map and sum effort records to work items
Data Collection Form
Enter total effort for 6.3.6 Information Management Activities

Figure 19: Data Collection Process for Project Management Effort Data (Continued)



Information Management Effort was entered
Project Plan
WBS Dictionary
Identify work items related with 6.3.7 Measurement Activities
Cubit Application
Work Break Down Structure
Project Schedule
Map and sum effort records to work items
TimeSheet Application (Effort Records)
Enter total effort for 6.3.7 Measurement Activities
Data Collection Form
Measurement related effort was entered
calculate total sum of project management activities
Data Collection Form
Total sum entered

Figure 19: Data Collection Process for Project Management Effort Data (Continued)

4.2. Data Collection Process for Requirements' Activities Effort Data

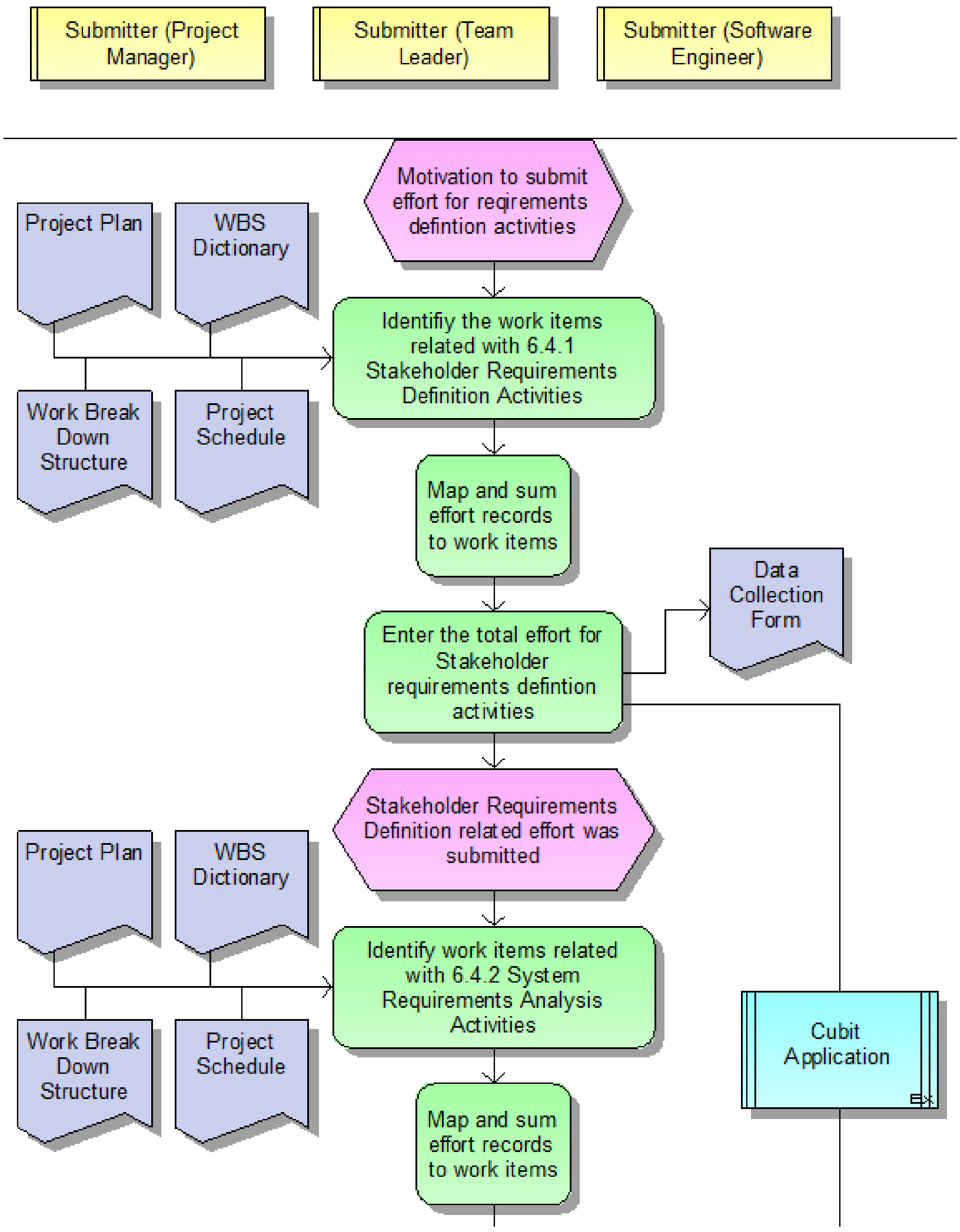

Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit effort for reqirements defintion activities
Project Plan
WBS Dictionary
Work Break Down Structure
Project Schedule
Identifiy the work items related with 6.4.1 Stakeholder Requirements Definition Activities
Map and sum effort records to work items
Data Collection Form
Enter the total effort for Stakeholder requirements defintion activities
Stakeholder Requirements Definition related effort was submitted
Project Plan
WBS Dictionary
Work Break Down Structure
Project Schedule
Identify work items related with 6.4.2 System Requirements Analysis Activities
Cubit Application
Map and sum effort records to work items

Figure 20: Data Collection Process for Requirements' Activities Effort Data

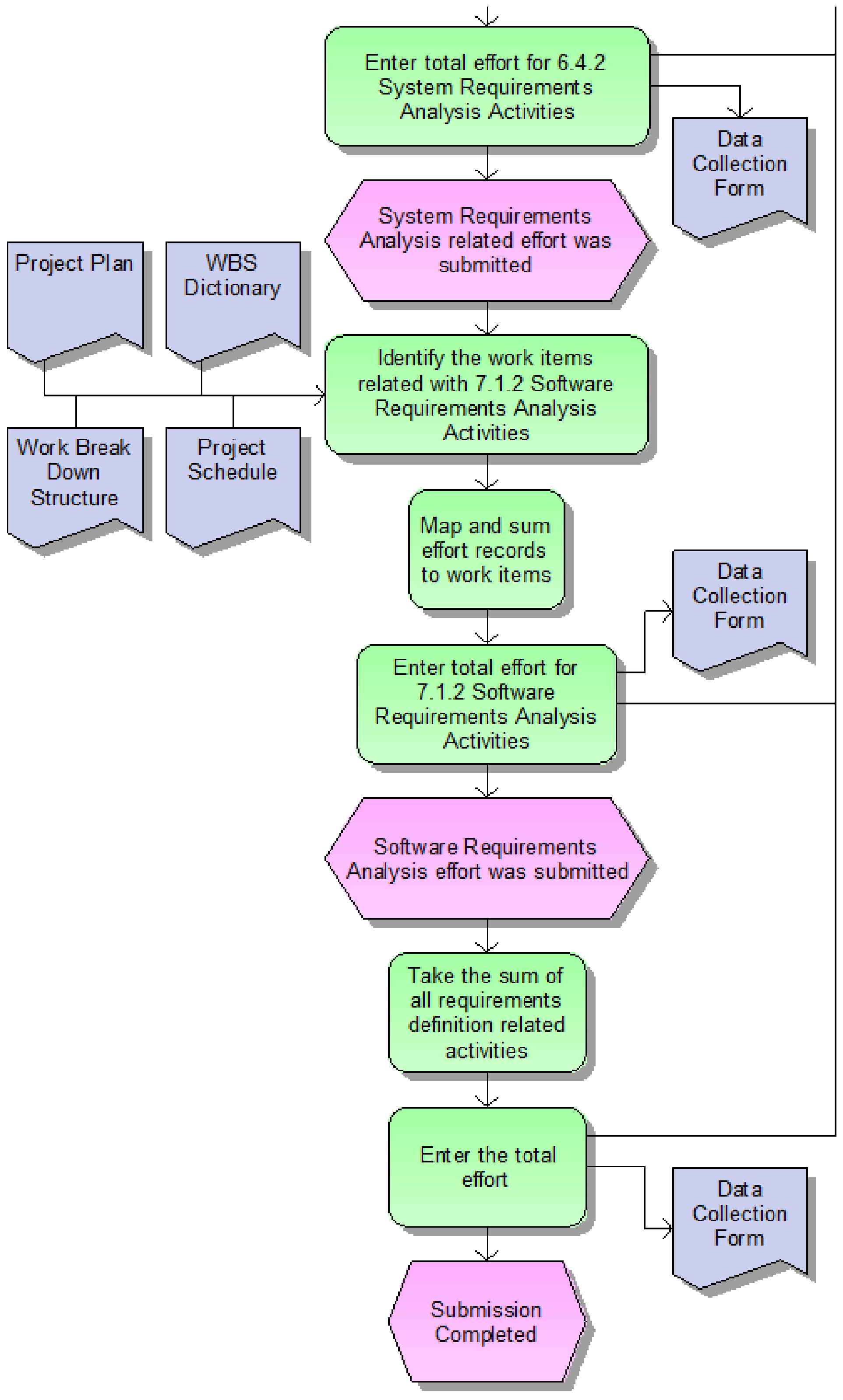
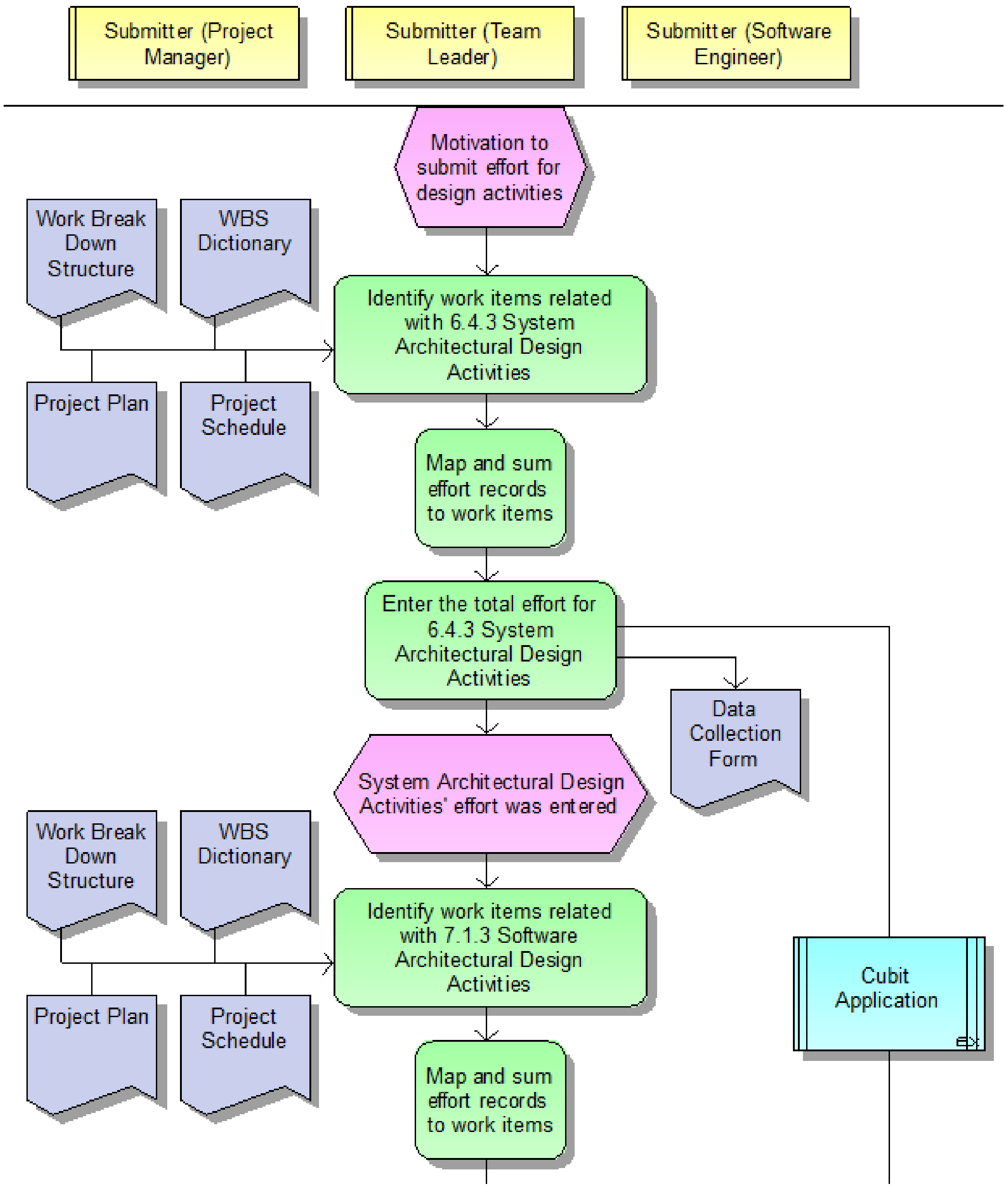

Enter total effort for 6.4.2 System Requirements Analysis Activities
Data Collection Form
System Requirements Analysis related effort was submitted
Project Plan
WBS Dictionary
Identify the work items related with 7.1.2 Software Requirements Analysis Activities
Work Break Down Structure
Project Schedule
Map and sum effort records to work items
Data Collection Form
Enter total effort for 7.1.2 Software Requirements Analysis Activities
Software Requirements Analysis effort was submitted
Take the sum of all requirements definition related activities
Enter the total effort
Data Collection Form
Submission Completed

Figure 20: Data Collection Process for Requirements' Activities Effort Data (Continued)

4.3. Data Collection Process for Design Activities’ Effort Data



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit effort for design activities
Work Break Down Structure
WBS Dictionary
Project Plan
Project Schedule
Identify work items related with 6.4.3 System Architectural Design Activities
Map and sum effort records to work items
Enter the total effort for 6.4.3 System Architectural Design Activities
Data Collection Form
System Architectural Design Activities' effort was entered
Work Break Down Structure
WBS Dictionary
Project Plan
Project Schedule
Identify work items related with 7.1.3 Software Architectural Design Activities
Cubit Application
Map and sum effort records to work items

Figure 21: Data Collection Process for Design Activities’ Effort Data

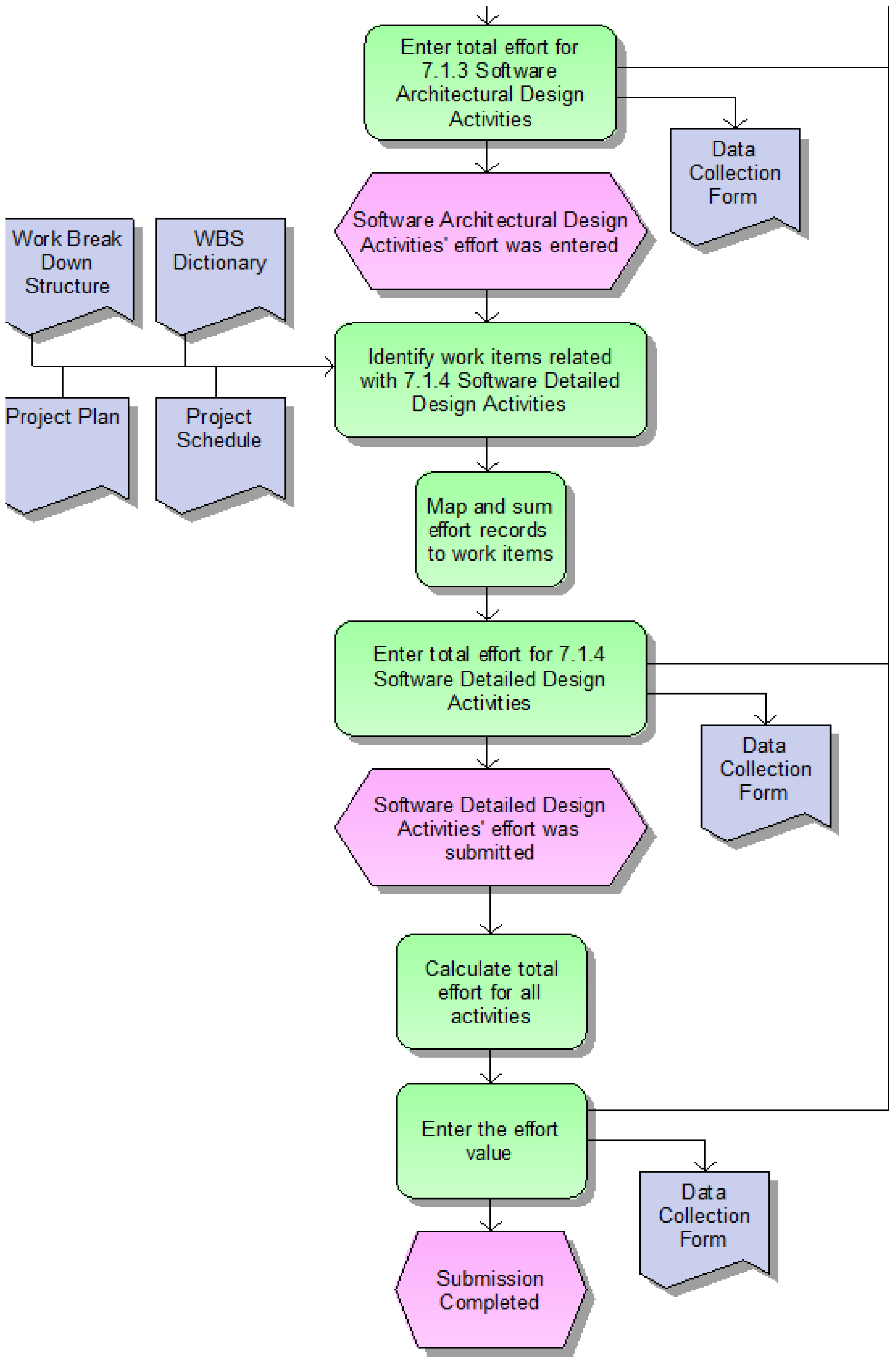
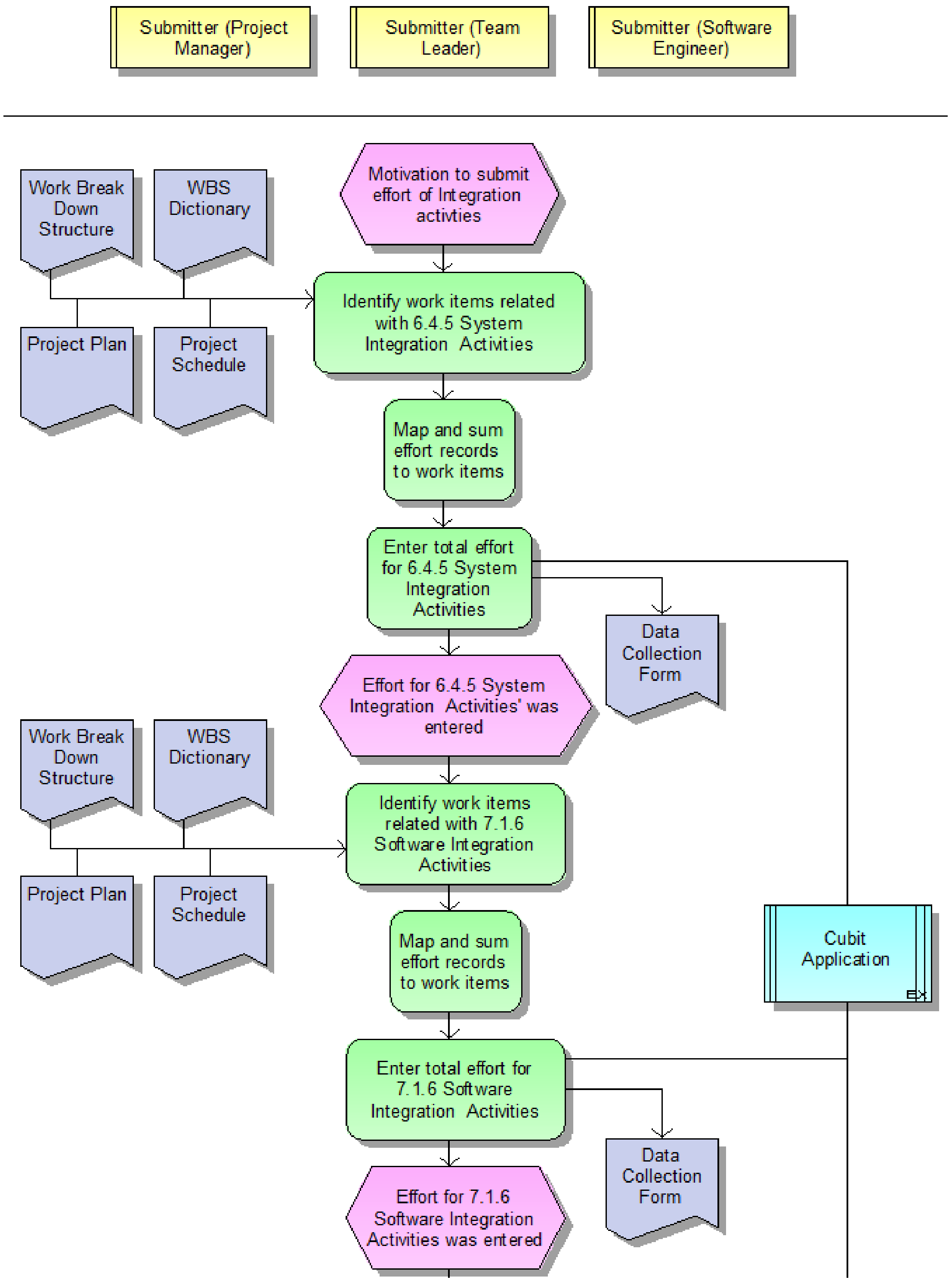

Enter total effort for 7.1.3 Software Architectural Design Activities
Data Collection Form
Software Architectural Design Activities' effort was entered
Work Break Down Structure
WBS Dictionary
Project Plan
Project Schedule
Identify work items related with 7.1.4 Software Detailed Design Activities
Map and sum effort records to work items
Enter total effort for 7.1.4 Software Detailed Design Activities
Data Collection Form
Software Detailed Design Activities' effort was submitted
Calculate total effort for all activities
Enter the effort value
Data Collection Form
Submission Completed

Figure 21: Data Collection Process for Design Activities' Effort Data (Continued)

4.4. Data Collection Process for Integration Activities' Effort Data



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Work Break Down Structure
WBS Dictionary
Project Plan
Project Schedule
Motivation to submit effort of Integration activties
Identify work items related with 6.4.5 System Integration Activities
Map and sum effort records to work items
Enter total effort for 6.4.5 System Integration Activities
Data Collection Form
Effort for 6.4.5 System Integration Activities' was entered
Work Break Down Structure
WBS Dictionary
Project Plan
Project Schedule
Identify work items related with 7.1.6 Software Integration Activities
Map and sum effort records to work items
Cubit Application
Enter total effort for 7.1.6 Software Integration Activities
Data Collection Form
Effort for 7.1.6 Software Integration Activities was entered

Figure 22: Data Collection Process for Integration Activities' Effort Data

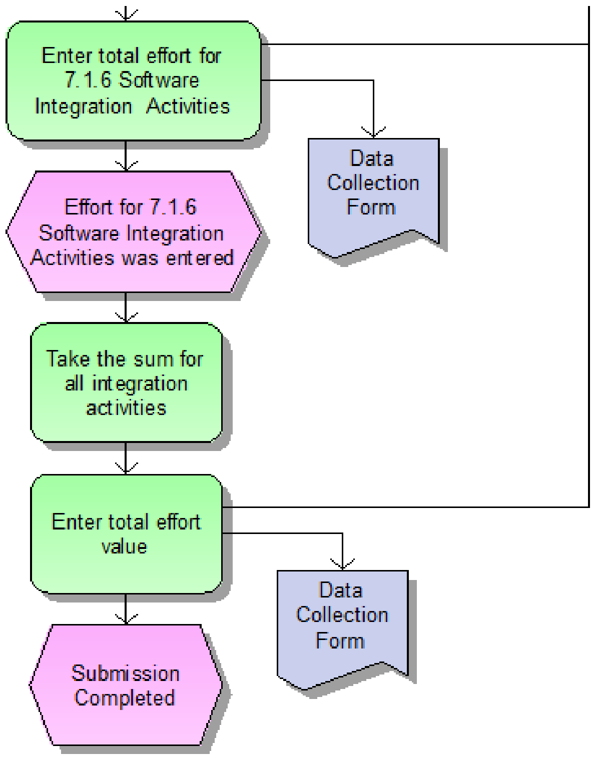
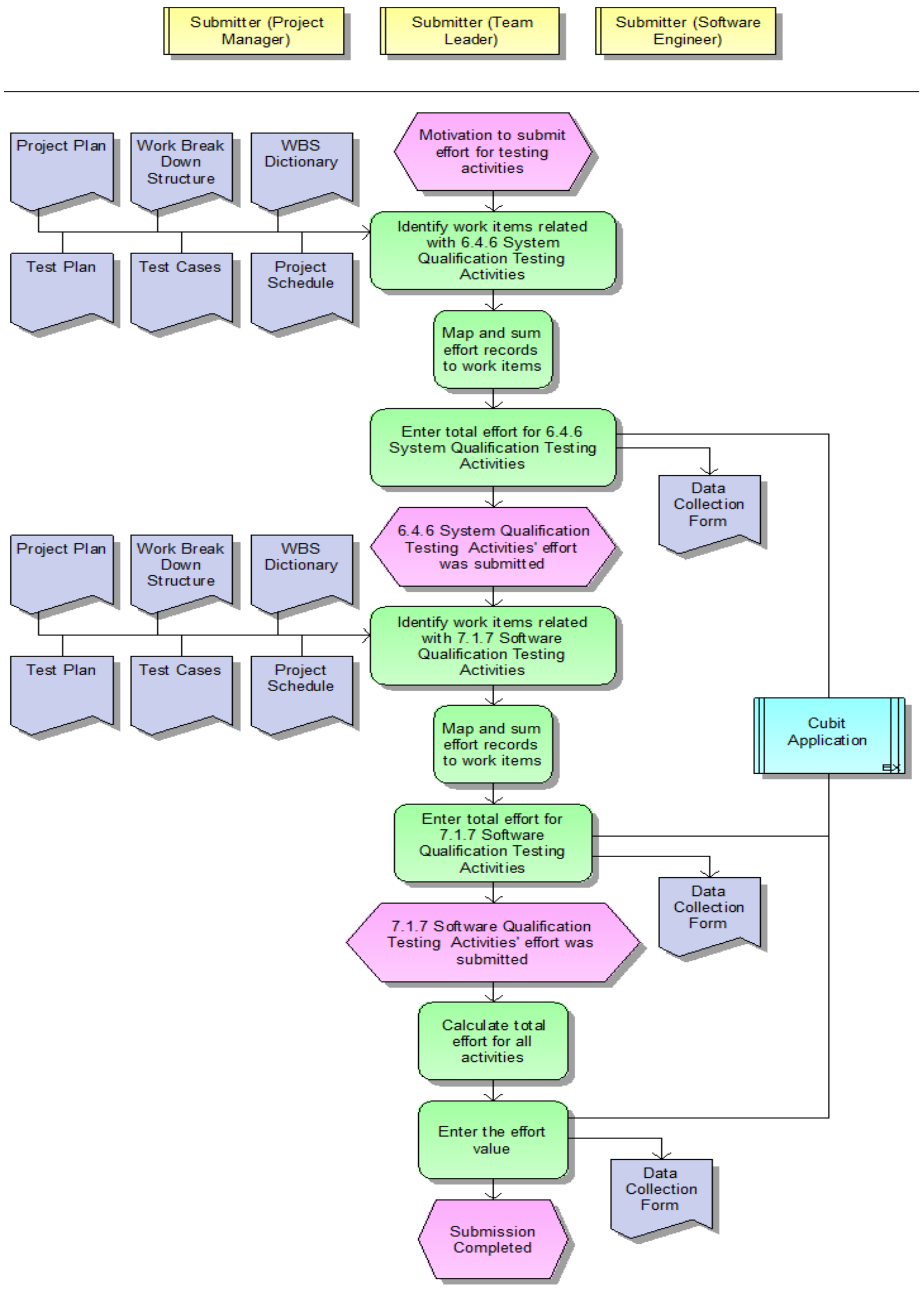

Enter total effort for 7.1.6 Software Integration Activities
Data Collection Form
Effort for 7.1.6 Software Integration Activities was entered
Take the sum for all integration activities
Enter total effort value
Data Collection Form
Submission Completed

Figure 22: Data Collection Process for Integration Activities' Effort Data (Continued)

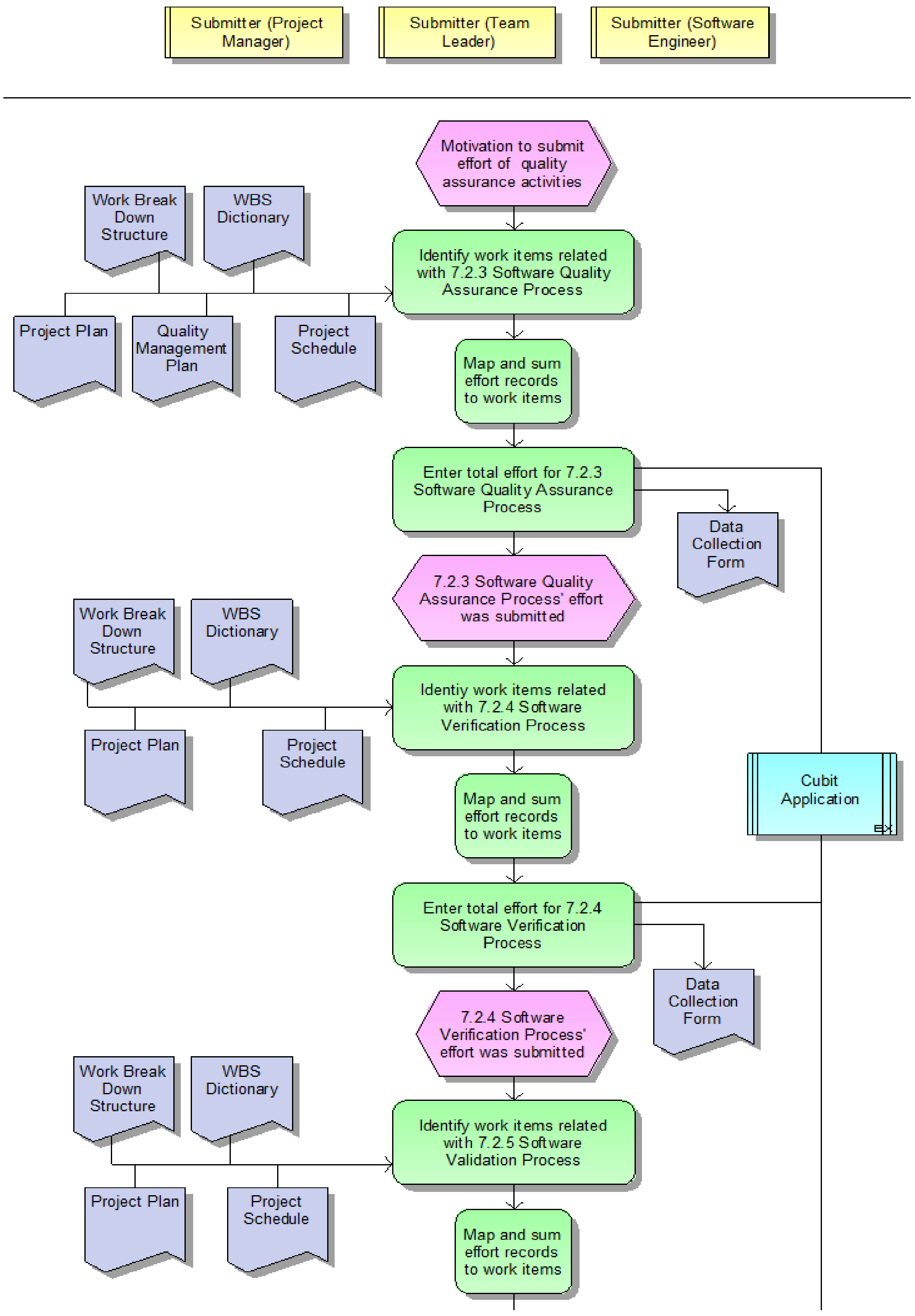
4.5. Data Collection Process for Test Activities' Effort Data



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Project Plan
Work Break Down Structure
WBS Dictionary
Test Plan
Test Cases
Project Schedule
Motivation to submit effort for testing activities
Identify work items related with 6.4.6 System Qualification Testing Activities
Map and sum effort records to work items
Enter total effort for 6.4.6 System Qualification Testing Activities
Data Collection Form
6.4.6 System Qualification Testing Activities' effort was submitted
Project Plan
Work Break Down Structure
WBS Dictionary
Test Plan
Test Cases
Project Schedule
Identify work items related with 7.1.7 Software Qualification Testing Activities
Map and sum effort records to work items
Cubit Application
Enter total effort for 7.1.7 Software Qualification Testing Activities
Data Collection Form
7.1.7 Software Qualification Testing Activities' effort was submitted
Calculate total effort for all activities
Enter the effort value
Data Collection Form
Submission Completed

Figure 23: Data Collection Process for Test Activities' Effort Data

4.6. Data Collection Process for Quality Activities' Effort Data



Submitter (Project Manager)
Submitter (Team Leader)
Submitter (Software Engineer)
Motivation to submit effort of quality assurance activities
Work Break Down Structure
WBS Dictionary
Identify work items related with 7.2.3 Software Quality Assurance Process
Project Plan
Quality Management Plan
Project Schedule
Map and sum effort records to work items
Enter total effort for 7.2.3 Software Quality Assurance Process
Data Collection Form
7.2.3 Software Quality Assurance Process' effort was submitted
Work Break Down Structure
WBS Dictionary
Identiy work items related with 7.2.4 Software Verification Process
Project Plan
Project Schedule
Cubit Application
Map and sum effort records to work items
Enter total effort for 7.2.4 Software Verification Process
Data Collection Form
7.2.4 Software Verification Process' effort was submitted
Work Break Down Structure
WBS Dictionary
Identify work items related with 7.2.5 Software Validation Process
Project Plan
Project Schedule
Map and sum effort records to work items

Figure 24: Data Collection Process for Quality Activities' Effort Data

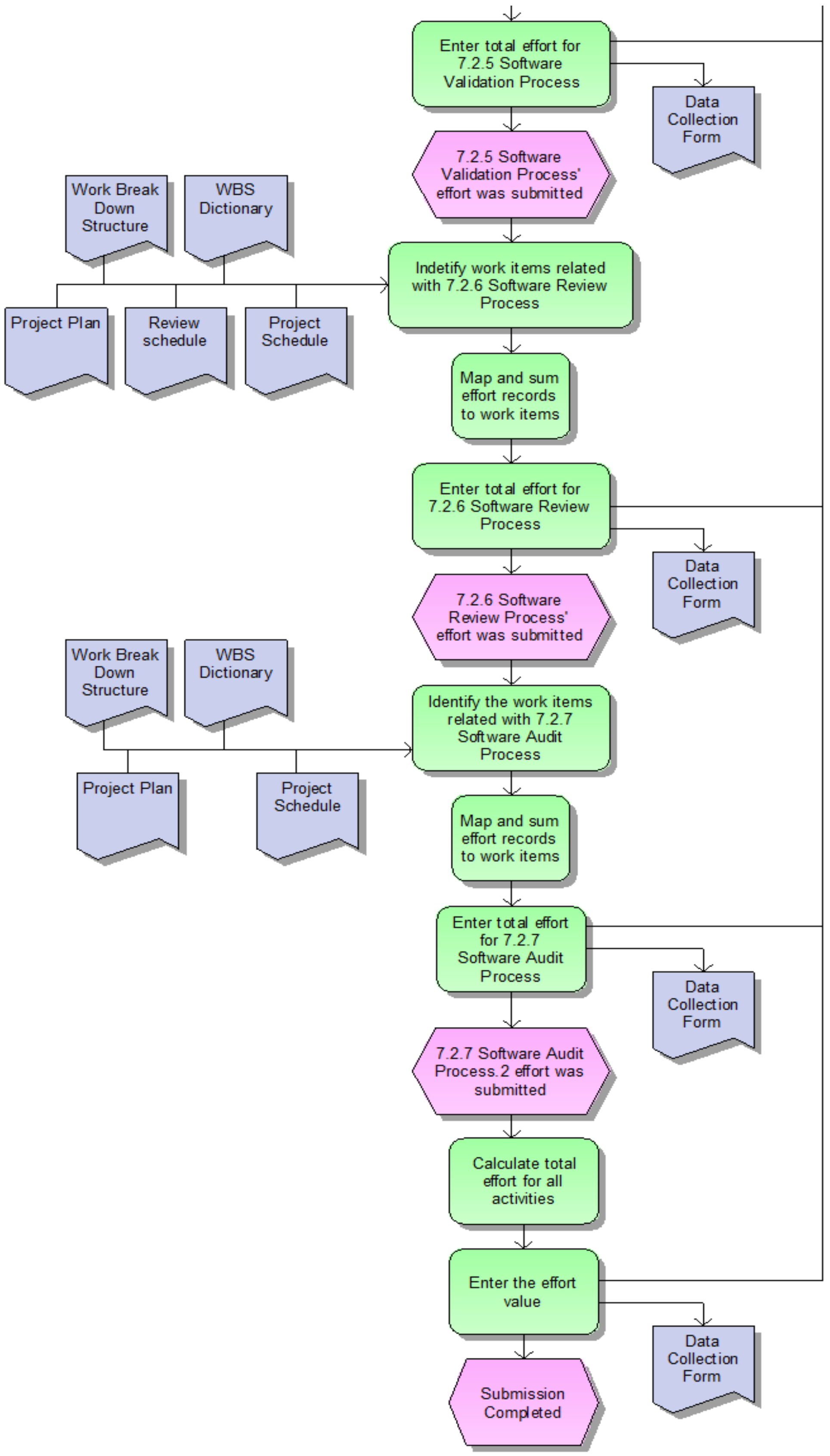

Enter total effort for 7.2.5 Software Validation Process
Data Collection Form
7.2.5 Software Validation Process' effort was submitted
Work Break Down Structure
WBS Dictionary
Indetify work items related with 7.2.6 Software Review Process
Project Plan
Review schedule
Project Schedule
Map and sum effort records to work items
Enter total effort for 7.2.6 Software Review Process
Data Collection Form
7.2.6 Software Review Process' effort was submitted
Work Break Down Structure
WBS Dictionary
Identify the work items related with 7.2.7 Software Audit Process
Project Plan
Project Schedule
Map and sum effort records to work items
Enter total effort for 7.2.7 Software Audit Process
Data Collection Form
7.2.7 Software Audit Process.2 effort was submitted
Calculate total effort for all activities
Enter the effort value
Data Collection Form
Submission Completed

Figure 24: Data Collection Process for Quality Activities' Effort Data (Continued)

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Sosyal Bilimler Enstitüsü	☐
Uygulamalı Matematik Enstitüsü	☐
Enformatik Enstitüsü	☐
Deniz Bilimleri Enstitüsü	☐

YAZARIN

Soyadı : ....
Adı : ....
Bölümü : ....

TEZİN ADI (İngilizce) : ....
....
....
....
....

TEZİN TÜRÜ : Yüksek Lisans ☐ Doktora ☐

1. Tezimin tamamı dünya çapında erişime açılsın ve kaynak gösterilmek şartıyla tezimin bir kısmı veya tamamının fotokopisi alınsın. ☐

2. Tezimin tamamı yalnızca Orta Doğu Teknik Üniversitesi kullancılarının erişimine açılsın. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) ☐

3. Tezim bir (1) yıl süreyle erişime kapalı olsun. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) ☐

Yazarın imzası .... Tarih ....