Analyzing the Performance of Two COSMIC Sizing Approximation Techniques Using FUR at the Use Case Level

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Abstract. For accurate results, standards for the measurement of the functional size of software require that the functionality to be measured be fully known. However, when estimating in the early phases of software development where there is a lack of detail, approximate sizing techniques must be used. An approximation mechanism that has proven useful when there is no historical data is the technique of approximation by EPCU, there are two EPCU contexts with the range of the output variable other than 16.4 CFP and 44 CFP.

Previous studies have shown that when functional requirements are at a granularity level of Functional Process, the context recommending being applied is that the output variable has a cut-off at 16.4 CFP, this is done when comparing the distribution of approximation results against the distribution of the REAL sizes. This paper investigates the two EPCU contexts defined in the literature, seeking to identify which technique appears to better represent the distribution of the REAL sizes when the granularity level was Use Cases (UC), the 'Equal Size Bands' (ESB) approximation and fuzzy logic-based approximation technique (EPCU) were also compared to identify which technique appears to represent the distribution of the REAL sizes better, when the granularity level was Use Cases (UC).

From the results, it is not clear which approximation technique has the best performance, however carrying out the non-parametric test, it is possible to confirm statistically that the distribution of the EPCU44 approximation technique displays behavior similar to that of the distribution of the COSMIC REAL sizes.

Keywords. COSMIC ISO 19761; Approximate Sizing; Functional Size; EPCU Model.

1 Introduction

Functional Size Measurement (FSM) methods work best when the information to be measured – the functional user requirements – is fully known. Santillo [1], for instance, indicates that the "functional size of software to be developed can be measured precisely [only] after the functional specification stage: this stage is often completed relatively late in the development process." However, when estimating in the early phases of software development projects, there is often a lack of detailed information, which hinders the rigorous application of the measurement rules prescribed in international standards [1, 2, 3].

As observed by Desharnais et al. [4], when software documentation is lacking, it is not possible to apply all of the detailed measurement rules as specified in the international standards for the measurement of the functional size of software. Thus, in such early phases of the development cycle, to tackle this lack of detail and determine a relevant range of candidate functional size, measurers must fall back on approximation techniques for sizing requirements.

As Vogelezang points out [5], "a rapid size measurement will be acceptable if it can be produced faster and still can deliver a reliable approximation of the detailed size measurement."

Most currently available approximation techniques for sizing the functional size of software requiring calibration employ historical data for better results in local contexts, such as the Equal Size Bands (ESB) approach described in [11]. However, collecting such data may be both expensive and time-consuming [8], and approximation techniques based on historical data are of little use without such data. This situation frequently occurs in the software industry. Additionally, COSMIC size approximation techniques were initially developed with a small sample of Functional Process (FP)/Use Cases (UC).

To tackle this situation, a different approximation approach using fuzzy logic, referred to as the EPCU COSMIC size approximation technique was proposed by Valdés et al. [9, 10, 11]. This approach does not require local calibration and is useful when there are no historical data available. Additionally, it is less expensive than the calibration of the ESB approach or any other approximation approach that requires historical data [8, 9, 10].

Research on the EPCU size approximation technique has focused on two granularity levels [11, 12] of the Functional User Requirements (FUR) description: Functional Process [7] and Use Case [12], with different EPCU context definitions, especially about changing the domain of its output variable function.

In order to analyze which of both EPCU contexts utilized and previously documented [8, 9, 10] exhibits, a better performance for each granularity level of the FUR description, in 2017 Valdés [13] investigated and compared using non-parametric testing, which of the EPCU contexts (with upper size boundaries at 16.44 CFP[1] as defined in [9] and 44 CFP as defined in [10]) appears to better represent the distribution of the REAL sizes, when the granularity level description was Functional Process.

[1] In this paper when functional size unit is CFP, the version is v4.0.1.

This paper presents a case study with a more extensive set of Use Cases aiming to identify which of the approximation techniques (the ESB technique and the EPCU technique using two distinct upper size boundaries) perform best, which means, statistically demonstrating which values distribution from the approximation techniques is more similar to REAL functional size distribution employing the standard COSMIC method, when the functional requirements are at the granularity level of Use Cases, a situation that presents very often in the industry.

It is known that there is no standard definition for Use Case; however, it has been observed that frequently, Use Cases correspond to more than one Functional Process, considering the results in [13], where the EPCU context with upper size boundaries at 16.4 CFP (EPCU16.4) appears to represent the distribution of the REAL sizes better, and when the granularity level description was Functional Process, the hypothesis for this work was the following:

H: The EPCU context with upper size cut-off at 44 CFP (EPCU44) better represents the distribution of the REAL sizes, when the granularity level of the functional user requirements description was Use Cases.

The structure of this paper is organized as follows. Section II presents related work. Section III presents the experiment. Section IV presents the data including statistical analysis, while Section V, the conclusions with suggestions for further work.

2 Related work on functional size approximation techniques

2.1 Approximation techniques based on averages

The IFPUG Function Point Analysis approximation technique for sizing was initially proposed in 1992 by Bock [16]. In 1997, Meli [14] proposed two variants but did not report on their performance.

In 2003, Desharnais et al. [4] analyzed two approximation techniques commonly used in the industry: Function Points Simplified (FPS) [15], and Backfiring from lines of code [16]. Using the detailed data from this study (e.g., 90 business information projects from five organizations), the FPS technique, with average weights for each of the five function types of the IFPUG Function Points method, exhibited better performance (MMRE = 10.4%[2] and PRED (0.15) = 76.2), while results from the Backfiring approach were highly inconsistent.

In 2004, Conte et al. [3] extended the Early & Quick (E&Q) technique to the COSMIC FSM method and indicated that further tests would be needed to make adjustments to the proposal, or to confirm it. This E&Q technique is based on (direct) analogy and (derived) analysis. It is a human-based size approximation technique impacted by the ability to "recognize" which components of the system belong to the proposed classes [17].

Since 2007, in the COSMIC document "Related Topics" [18] that evolved in 2015 into the COSMIC Guideline for Early or Rapid COSMIC Functional Size Measurement

[2] MMRE, PRED(0.15) calculations using the detailed data from [4]

[6], two approximation techniques were based on averages where documented: the average Functional Process approach, and the average Use Case approach.

2.2 Approximation techniques based on size bands

In 2007, in a study of 50 projects, Vogelezang et al. [5] reported on a proposed size approximation technique based on size bands using the quartile approach. The authors also investigated the influence of distinct factors in approximate sizing and reported that, within this sample, the sole factor that exerted a substantial influence on the size of an average Functional Process in each of the quartiles was the number of Functional Processes [5]. In their case study, a reference software system with a full set of stable requirements and stated measured functional size was available.

In general, an approach to approximate the size of a scaling factor for FUR type(s) of artifact(s) must be defined locally [18]. This requires, for instance, that an average size of the artifacts to be measured be established locally.

This scaling factor represents the size that one can expect to be measured when FUR are at a level of detail where an accurate measurement can be made because all necessary details are available [5]. This solution requires historical data to produce an adequate scaling factor. In 2011, Santillo [1] proposed the Early and Quick COSMIC sizing approximation, based on earlier work [3] and the Analytic Hierarchy Process [19], a technique, which provides a means for making choices among sizing alternatives.

In 2013, Almakadmeh [17] designed a framework to assign scaling factors for identifying the granularity level of documentation of the functional requirements. Two variants of criteria for assessing granularity levels were defined: the first considered a functional component of software, and the second, the elements of a UML use-case model. To rank the levels of granularity identified, the scaling factors used in [5] were selected. Next, scaling factor assignment was based on conducting an analogy-based comparison with similar pieces of software in which the functional size of the software pieces was accurately measured using the COSMIC measurement method.

In 2014, De Vito et al. [20] proposed a simplified measurement process (Quick/Early) that addressed the need for a simplified and rapid COSMIC measurement avoiding the use of scaling factors, where incorrect calibrations of scaling factors can lead to inaccurate approximations. The Quick/Early approximation approach can be applied on Use Case models to reduce measurement time. Quick/Early precision is directly proportional to the granularity level of the Use Case model analyzed. This means that Use Cases require stable requirements that, however, do not occur too frequently in the early stages. Nonetheless, the authors concluded that Quick/Early accuracy is adequate.

2.3 Approximation techniques base on fuzzy logic

In 2012, Valdés et al. [9] proposed a COSMIC size approximation solution using a fuzzy logic model referred to as the Estimation of Projects in a Context of Uncertainty (EPCU) [2, 21, 22].

The advantages of the EPCU size approximation technique can be summarized as follows [8, 9, 10]:

- Does not require local calibration and is useful when there are no historical data available.
- Less expensive to calibrate than the ESB approach, which requires historical data.
- Exhibits good behavior, even when individuals are not acquainted with the COSMIC method.
- Exhibits good behavior, even when requirements are not fully known.
- Enables systematic replication of the information.

In these studies [2, 21, 22], two EPCU contexts were defined for a continuous range of possible values with a "natural" upper boundary, or cut-off instead of size bands, and a mixture of granularity levels (Functional Process and Use Case), simulating the early phases of the software life cycle:

1. The first EPCU context, defined a cut-off at 16.4 CFP [8, 9] (EPCU16.4), based on the ESB approach as defined by Vogelezang [5] (Small = 4.8 CFP, Medium =7.7 CFP, Large = 10.7 CFP, and Very Large = 16.4 CFP), and
2. The second context defined a cut-off at 44 CFP [11] (EPCU44), defined after analyzing the database used by Vogelezang [5], that contains two general analyses over the functional process measured labeled Q-Size and Q-Number. Considering the Q-Size where the total measured size is divided into quartiles and the average FP size is calculated from each one (Q_1=3.7 CFP, Q_2=7.7 CFP, Q_3=14.6 CFP and Q_4=44.1 CFP)

For this new study, it is considered the integrated analysis, the concept of both is described below.

EPCU approach research also focused on the definition of the EPCU context, selecting several samples from case studies, usually an industry or reference project with fewer than 12 practitioners, focusing on analyzing the performance of the approximation technique in the early phases.

For instance, Valdés et al. [10] reported on a case study of a simulation of early approximation using the EPCU model for an industry project for which only the names of the Use Cases were made available to participants. This case study confirmed that the EPCU size approximation approach does not require local calibration and is useful when there are no historical data available. Besides, it proved less expensive than calibration of the ESB approach, which requires historical data. In this case study, the output variable was defined for a continuous range of possible values with an upper boundary, or cut-off instead of size bands, at 16.4 CFP, as per the ESB approach defined by Vogelezang et al. [5]. For a case study with a REAL industrial project, the EPCU size approximation technique yielded better results than the ESB approach, while both techniques led to lower sizes than the real functional size.

In 2015, Valdés et al. [11] proposed another version of their fuzzy logic size approximation technique. It defined a continuous range of possible values for the output variable with an upper Q4 (4th Quartile) cut-off of 44 CFP for a Functional Process using the dataset of Vogelezang et al. [5]. For the study of an industry project that considered Use Case granularity level, the EPCU cut-off at 44 CFP [11] yielded better results on comparison with the ESB approach and EPCU cut-off at 16.4 CFP [10]. The Functional size was underestimated for Functional Process or Use Cases using the EPCU cut-off at 16.4 CFP. On the other hand, results were above and below the REAL value for Use Cases using the EPCU cut-off at 44 CFP. More realistic results were obtained using the EPCU44.

Research on the EPCU size approximation technique has focused on two granularity levels [11, 12] of the FUR description: Functional Process [7], and Use Case [12], using two EPCU context definitions; however, it was not clear when to utilize each EPCU context (EPCU16.4, EPCU44), in order to analyze which of the two has a better performance for each granularity level of functional requirements. In 2017, Valdés [13] investigated and compared using a non-parametric test, which of the EPCU contexts appeared to represent the distribution of the REAL sizes better, when the granularity level was Functional Process.

In the study [13], it was statistically demonstrated that distribution for approximation values using EPCU16.4 was similar to REAL value distribution employing the standard COSMIC method with 180 Functional Process.

There is no standard definition for Use Case, and it has been observed that frequently that Use Cases involve more than one Functional Process, sounds logical that the EPCU approximation technique with a cut-off of 44 CFP might be more useful if functional requirements are at the granularity level of Use Cases, a situation that occurs very frequently in the industry. However, based on the findings of [13], the valid conclusion is that the EPCU44 approach is not as useful with the Functional Process level of granularity, as it leads to oversizing, and a similar assessment, but employing Use Cases, is proposed as further work.

2.4 Smmary of COSMIC approximation techniques

The validity of the majority of approximation techniques is dependent on the representativeness of the samples with respect to the software being approximated. In other words, the majority of approximation methods require local calibration, and this requires local historical data. Even more COSMIC size approximation techniques were initially developed with a small sample of data. However, as pointed out by Morgenshtern [8]: “Algorithmic models need historical data, and many organizations do not have this information. Additionally, collecting such data may be both expensive and time-consuming.” Approximation techniques based on historical data are of little use for organizations without such data. Alternatives must, therefore, be developed for such contexts of approximation.

The COSMIC Guideline for Early or Rapid COSMIC Functional Size Measurement [6] integrates several techniques for the approximate sizing of new, ‘whole’ sets of requirements. The approximation techniques described in [6] include approximation techniques based on size bands or based on average.

The majority of the techniques presented in [6] are based on the existence of historical data to determine the scaling factor (average, or size bands) or another calibration, and that there are stable requirements [11].

2.5 Impact of approximated size on the estimation of effort

In 2013, De Marco et al. [23] investigated to what extent some COSMIC-based approximate sizing could be useful for project managers for early effort estimation for Web applications. The authors reported an empirical analysis employing data from 25 Web applications to assess whether two approximate sizes (number of COSMIC Functional Processes (FP) or the Average Functional Process approach) could be exploited to acquire accurate effort estimates. These authors concluded that COSMIC-based approximate sizing was a suitable approach for early effort estimates, while estimates obtained with approximate sizes were worse than those achieved employing the size obtained from the application of the standard COSMIC method.

3 Experiment with approximation techniques

This section describes the experiment carried out to evaluate the size approximation techniques and identify which technique appears to represent the distribution of the REAL sizes better, when the granularity level was Use Cases (UC).

3.1 Context and participants

As a part of a consultancy project whose objective was to implement the use of COSMIC for a Government entity in Mexico carried out in 2016, with the objective of generating formal estimation models, several projects were measured using the COSMIC method.

The three main circumstances described in [6], in which only an approximate COSMIC functional size may be possible were presented in the project:

- When a size measurement is needed rapidly, and an approximate size measurement is acceptable if it can be measured much faster than with the standard method. This is known as 'rapid sizing';
- Early in the life of a project before the actual requirements have been specified in enough detail for precise size measurement. This is known as 'early sizing';
- In general, when the quality of the documentation of the actual requirements is not sufficiently good for precise size measurement.

Considering the information below, the functional size for the projects was gathered using the approximation approaches as the first step and then, when the required detail for the requirements was accomplished, the full standard was used to obtain the functional size.

To conduct a comparison with the previous study [13] focused on 180 Functional Process, four projects were selected. These four projects integrated 293 Use Cases that were approximated using ESB and EPCU techniques.

The people in the Government entity received 24 hours of training in COSMIC during the consultancy project, including the EPCU approximation technique and that of equal size bands. The information required for using the approximation techniques were required from the technical people, specifically from the project leader for each project, with a distinct project leader for each project.

It is important to mention that the techniques related to the Requirements Engineering used by the Government entity was not affected by the consultancy and was possible to observe that sometimes the Use Cases include much functionality. Table 1 shows the number of Use Cases by project.

Table 1. Use Cases by project considered in the case study

ID Project	# UC Assigned
1	43
2	96
3	55
4	99
Total	293

3.2 Participant instructions for functional size measurement and approximation

Each project leader was asked to perform the following:

1. Identify, for each project, the set of Use Cases assigned to be developed.
2. Classify (using expert judgment) by size each of the Use Cases using the following linguistic values: Small; Medium; Large, and Very Large[3].
3. Classify (using expert judgment) the number of objects of interest for each of the Use Cases using the following linguistic values: Few; Average, and Many.
4. Assign values (using expert judgment) in the range 0 - 5 ε R for the two previously classified input variables (points 2 and 3, the Use Cases' size, the number of objects of interest related to the Use Cases) defined within the EPCU context, considering the subjective classification relative to the functional size of the Use Cases (e.g., Step 2), and the subjective classification for the number of objects of interest in each Use Case (e.g., Step 3).

[3] The linguistic values were defined in concordance to the ESB Approach to enabled the comparison.

5. Measure functional size using the COSMIC method and provide the size for each Use Case.

3.3 Data collected by participants

Project leaders identified 293 Use Cases in four projects (Table 1), and the data provided by the project leaders were the following (see Appendix I for details):

- A value assigned within the range of 0 - 5 ε R for the size of each Use Case.
- A value assigned within the range of 0 - 5 ε R for the objects of interest for each Use Case.
- COSMIC size using the COSMIC method for each Use Case.

The linguistic classification of the Use Cases and the linguistic classification of the objects of interest for each Use Cases (data from Steps 2 and 3) were not included in the table in the Appendix since the input for the EPCU approximation approach were the values assigned for each variable (data from Step 4).

3.4 Researcher steps

Using the linguistic classification (Small, Medium, Large, and Very Large) assigned by the participants for the Use Cases the ESB technique was performed.

Using the values (between 0 and 5) assigned by the participants for the two input variables of the fuzzy logic based EPCU approximation technique, CFP units were performed by the researcher using the EPCU approximation technique with distinct EPCU contexts (EPCU16.4 and EPCU44) defined in [8, 9] and [11].

The COSMIC size approximated with the data provided by the project leaders was verified using the COSMIC measurement principles and rules by two consultants with more than 7,000 CFP measurement experiences at the verification moment.

COSMIC functional size and approximate size for each Use Case are presented in Appendix II where:

- Column 1 presents the Project identifier. For confidential purposes, the Projects were labeled sequentially, from "Proj 1" to "Proj 4.
- Column 2 presents the Use Case identifier. For confidential purposes, the Use Cases were labeled sequentially, from "UC 1" to "UC 293.
- Column 3 presents the functional size obtained utilizing the standard COSMIC method – in CFP units,
- Column 4 presents the Equal Size Band approximation approach,
- Column 5 presents the EPCU size approximation approach using an output variable domain function from 2 - 16.4 CFP [8] [9], and
- Column 6 presents the EPCU size approximation approach using an output variable domain function from 2 - 44 CFP [10].

4 Data Analysis

4.1 Quality Criteria

Three most frequently quoted quality criteria [24] were used to analyze the behavior of the two approximation techniques :

- Mean Magnitude of Relative Error (MMRE),
- Standard Deviation of MRE (SDMRE), and
- Prediction level, here PRED(25%) was selected.

The Median Magnitude of Relative Error (MdMRE) is also used. The primary advantage of the median over the mean is that the median is not sensitive to the outliers.

Table 2 presents the results for each of these quality criteria for each approximation approach (top line) for the set of 293 Use Cases:

1. With an MMRE of 61.4%, the ESB presented the best results (in comparison to MMRE = 65.7% with the EPCU16.4 technique and MMRE = 117.4% with EPCU44).
2. With an SDMRE of 49.1%, ESB presents the best results, in comparison to SDMRE of 62.2% for the EPCU16.4 technique and SDMRE = 156.1% for the EPCU44 technique.
3. Within a PRED (25%) at 20.8%, the EPCU with a cut-off at 44 CFP presents the best results, in comparison to 18.8% with ESB and 17.1% with EPCU with the cut-off at 16.4 CFP.
4. With a MdMRE of 56.9%, the EPCU16.4 technique presents the best results, in comparison to 59.5% with ESB and 63.3% with EPCU with a cut-off of 44 CFP. It is possible to observe that the difference between the maximal and the minimal MdMRE values are less than the other quality criteria.

Two quality criteria present the best results in the ESB approach (MMRE and SDMRE); however, the prediction level presents the best results for the EPCU with the cut-off at 44 CFP, and the MdMRE presents the best results for the EPCU16.4.

Table 2. Approximation technique performance for 293 Use Cases

	ESB	EPCU 16.4	EPCU 44
MMRE	61.4%	65.7%	117.4%
MdMRE	59.5%	56.9%	63.3%
SDMRE	49.1%	62.2%	156.1%
PRED(25%)	18.8%	17.1%	20.8%

From the quality criteria, it is not clear which approximation technique has the best performance, this because the central tendency measurements are affected by outliers.

MMRE has been shown to be a biased estimator of central tendency of the residuals of a prediction system because it is an asymmetric measure [25], [26], [27], [28]. Shepperd et al. [29] proposed the Mean Absolute Residual (MAR), which, unlike MMRE, is not biased to compare the accuracy of a given estimation method *P* against the accuracy of a reference estimation method *P0*.

$$\text{MAR} = \frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}i| \quad (1)$$

Based on the calculated MARP (the MAR of the proposed method) and MAR*P0* (the MAR of a reference method), Shepperd et al. [29] propose to compute a Standardized Accuracy measure (SA) for estimation method P.

$$\text{SA} = 1 - \frac{MAR_P}{MAR_{P0}} \quad (2)$$

Where values of SA close to 1 indicate that *P* outperforms *P0*, values close to zero indicate that *P's* accuracy is similar to *P0's* accuracy, and the negative values indicate that *P* is worse than *P0*. The authors [29] suggest to use a referenced model random based considering the known (actual) values of previously measured projects, however, Lavazza [30] observed that the comparison with random estimation is not very effective in supporting the evidence that P is a good estimation model. Instead, proposed to use a "Constant Model" (CM), where the estimate of the size of the i^{th} project is given by the average of the sizes of the other projects, then the calculation of the MAR*CM* of these estimates is realized, and then the compute of SA, comparing method *P* with a method *CM*, generalizing that SA could be used to compare an estimation method *P* against any other method *P1* used as a reference method.

$$\text{SA} = 1 - \frac{MAR_P}{MAR_{P1}} \quad (3)$$

Table 3. Standardized Accuracy measure using the ESB as a reference (P1)

	EPCU 16.4	EPCU 44
MAR Calculated using (1), The MAR for ESB = 17.7	16.7	17.6
SA Calculated using (3) Considering ESB as P1	-0.96	-1.05

Table 3 presents the results related to the comparison between each EPCU context (top line), considering the Standardized Accuracy measure approach proposed for Lavazza [30], using the ESB approximation approach as CM as in (3). With a SA close to zero (0.05 for EPCU 16,4 and 0.01 for EPCU 44), both EPCU context present similar accuracy to the reference approximation approach (ESB). Considering the SA measure, the ESB present a better result, it is not clear which approximation technique has the best performance.

4.2 Graphical Analysis

Fig. 1 A), graphically presents, for each of the 293 Use Cases, the REAL COSMIC size (in blue) and the size approximated with the ESB technique (in orange).

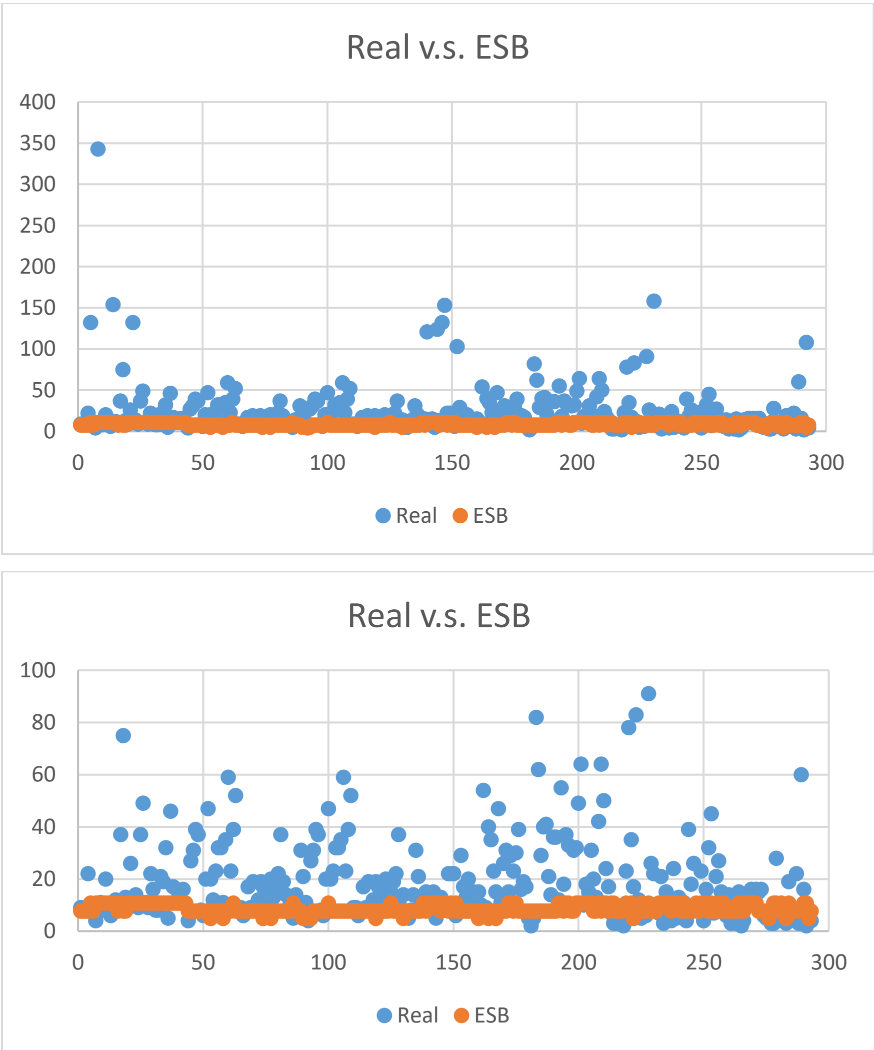

Fig. 1. REAL COSMIC size vs. approximated size using the ESB technique – 293 Use Cases. A) Vertical axis boundaries at 400 CFP. B) Vertical axis boundaries at 100 CFP.

Note that with the ESB technique, the only four values possible for the approximated size (in orange) are as follows: 4.8 CFP; 7.7 CFP; 10.7 CFP, and 16.4 CFP corresponding to the four average size bands of Functional Process (Small, Average, Large, and Very Large).

From the data (Appendix II, column 3), it is possible to conclude that 230 Use Cases (78.5%) were underestimated; in consequence, overestimated 63 Uses Cases are (21.5%). From these overestimated Use Cases, 139 are due to that the upper boundary, or cut-off, was established at 16.4 CFP and the Use Cases had a functional size higher than that of the cut-off.

Fig. 2 depict the graphical comparison with the EPCU16.4 technique. This technique defines a continuous range of possible values between 2 CFP and an upper boundary or cut-off at 16.4 CFP; consequently, at least 139 Use Cases were underestimated because of the upper boundary.

Looking at the data from (Appendix II, column 3), overestimated Uses Cases numbered 99 (33.8%), while underestimated Use Cases numbered194 (66.2%). It is possible to observe that the number of Use Cases underestimated decrease in 36 Use Cases considering the ESB technique, and the Use Cases overestimated increase.

Fig. 3 presents the graphical comparison with the EPCU44 technique because this approach has a cut-off at 44 CFP; naturally, fewer Use Cases were underestimated, 130 (44.4%), while overestimated Use Cases numbered 163 (55.6%), and for the EPCU44 technique, more Uses Cases were overestimated.

Intuitively from the previous figures, the EPCU44 better represents the distribution of the REAL sizes; however, it is not easy to infer from Fig.1 to Fig. 3, because there are several outliers. This confirms the reason regarding the big difference between the maximal and the minimal values for MdMRE and MMRE from Table 2.

Considering the difference between MdMRE and MMRE, it is possible to assume that the distribution is skewed and that the most representative value is the MdMRE, because central tendency measurements were affected by the outliers.

In Fig. 4, the boxplots related to the REAL Value of functional size, and ESB, EPCU16.4, and EPCU44 functional size approximation, are presented. This is a better approach for analyzing the data without considering the outliers.

From Fig. 4, it might be easier to infer that EPCU44 better represent the distribution of the REAL sizes, because both boxplots are very similar.

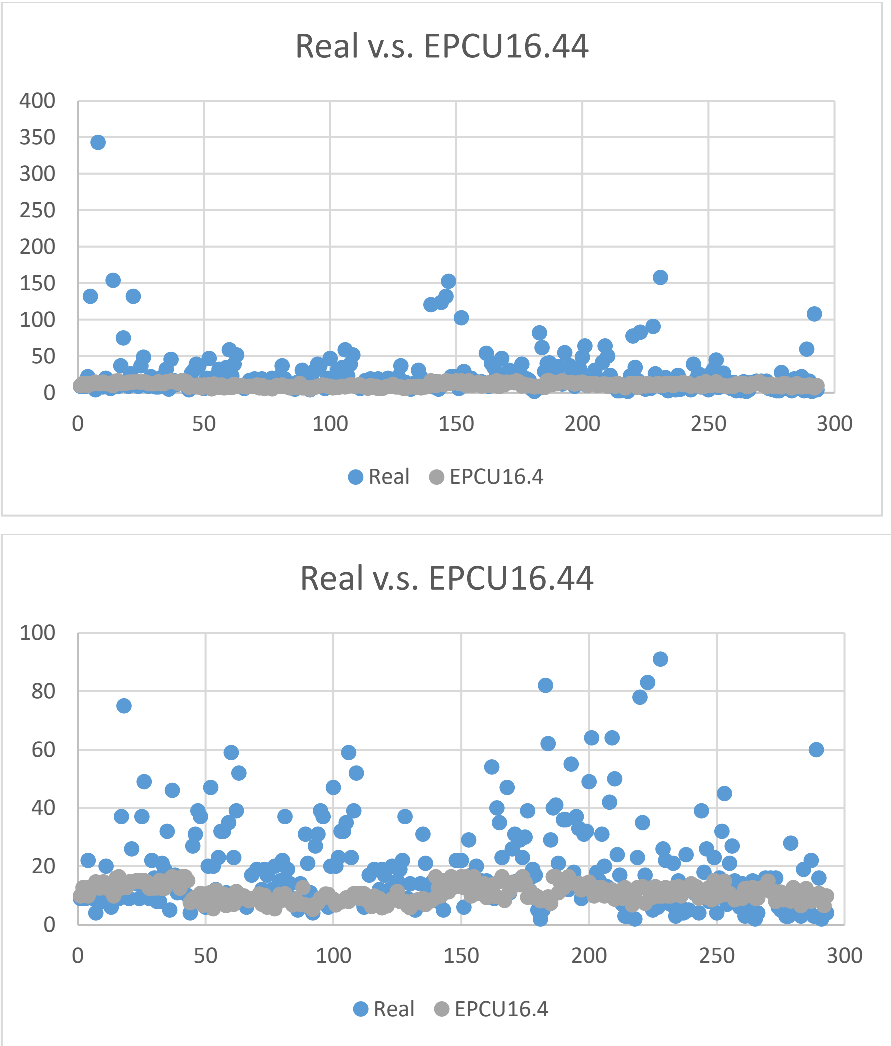

Fig. 2. REAL COSMIC size vs. approximated size using the EPCU-16.4 technique – 293 Use Cases. A) Vertical axis boundaries at 400 CFP. B) Vertical axis boundaries at 100 CFP.

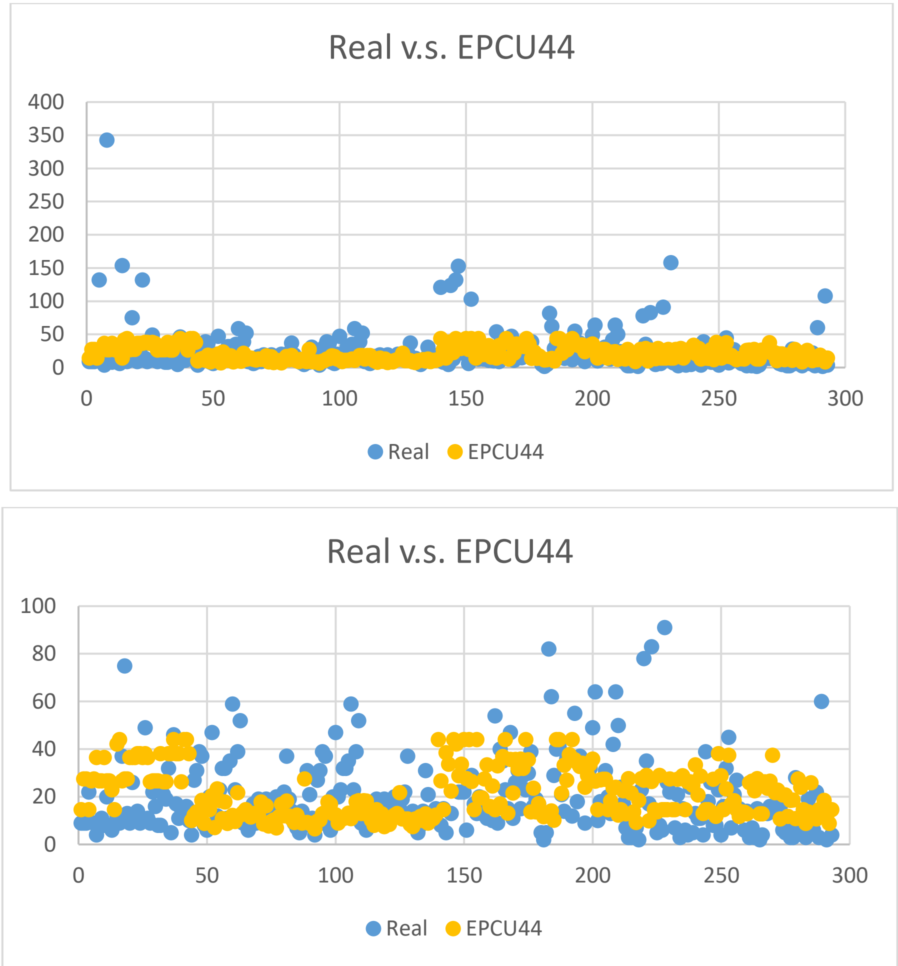

Fig. 3. REAL COSMIC size vs. approximated size using the EPCU-44 technique – 293 Use Cases. A) Vertical axis boundaries at 400 CFP. B) Vertical axis boundaries at 100 CFP

4.3 Non-parametric test

Considering the quality criteria affected by the central tendency measurements, the approximation technique that provides better results was ESB. From the plots in Fig.s 1, 2, 3, and 4, the EPCU44 technique appears to better represent the distribution of the REAL sizes; however, this needs to be confirmed by statistical analysis.

In non-parametric statistics, a well-known procedure for testing the differences among more than two related samples is the Friedman test [24, 25] The objective of the test is to determine whether it can be concluded, from a sample of results, that there is a difference among treatment effects [32].

Using the Friedman non-parametric test to analyze whether there is a difference among the performances of distinct treatments across the same datasets for functional size, that is, whether the data distributions are equal, a null hypothesis H0 was defined as:

H0: There are NO meaningful differences in the distributions of REAL, ESB, EPCU16.4, and EPCU44 datasets.

In consequence, the alternative hypothesis was defined as:

H1: At least one distribution (REAL, ESB, EPCU16.4, and EPCU44) is significantly different. A significance level of α (alpha (α)) = 0.05 was assumed.

SPSS® version 22 software in the Spanish language was utilized to evaluate the Friedman test for the four distinct treatments (REAL, ESB, EPCU16.4, and EPCU44), and the results are summarized in Table 4. The full results from SPSS ® are presented in Appendix III.

In Table 4, "N" represents the 293 Use Cases, "df" represents the degrees of freedom (with four distinct treatments; the df is 3 (#treatments -1)). Here, the statistical significance ("Asymp. Sig." or p-value) is a very small number at E-101, thus below the required significance level of α =0.05.

Therefore, the null hypothesis (e.g., H0: There are NO meaningful differences in the distribution of REAL, ESB, EPCU 16.4, and EPCU 44) is rejected, and it is possible to state that at least one treatment has a distinct distribution.

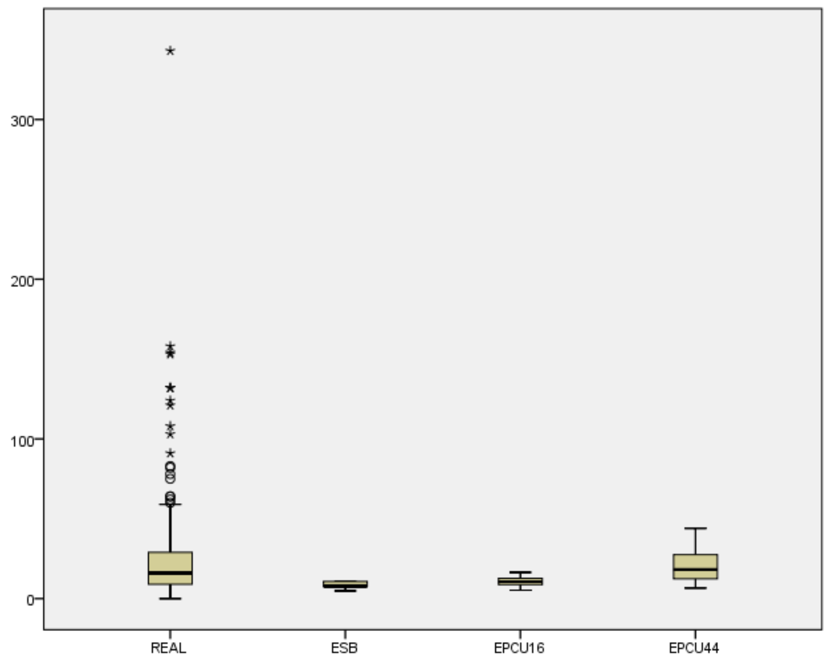

Fig. 4. Boxplots related to the REAL Value of functional size, and ESB, EPCU16.4, and EPCU44 functional size Approximation.

Table 4. Friedman test results on the testing of the four distributions (REAL, ESB, EPCU16.4, and EPCU44)

N	293
Chi-Square	468.936
df	3
Asymp. Sig.	2.5722E-101

In order to identify where the difference is, a post-hoc test is needed. In this instance, a post-hoc test assesses the difference between treatments as follows:

- REAL and ESB
- REAL and EPCU16.4
- REAL and EPCU44
- ESB and EPCU16.4
- ESB and EPCU44
- EPCU-16.4 and EPCU44

Here, the post-hoc test compared two treatments at a time. The Wilcoxon [32] test was executed using SPSS® software, and the Bonferroni correction [33] was considered; thus, the α value (α =0.05) was divided by 4 because four distinct treatments were used. This means that the α was reset at α =0.0125.

Considering the latter, the null hypothesis H0 for the post-hoc test was:

H0: There are NO meaningful differences between the distributions for the two treatments compared (see the previous list).

In consequence, the alternative hypothesis was defined as:

H1: The distribution for the two treatments compared is significantly different, assuming a significance level of α = 0. 0125.

Table 5 presents the results of applying the Wilcoxon test for two treatments in SPSS®. Column 1 indicates the comparison, and column 2, the significance for the Wilcoxon test. The significance value was compared with α = 0.0125 by accepting (>α = 0.0125) or rejecting (<α = 0.0125) the null hypothesis; the results are presented in column 3. The full results from SPSS® are presented in Appendix IV.

From Table 5, with a p-value of α =0.0125, it is possible to confirm statistically that only the distribution of the EPCU44 approximation technique (with a cut-off at 44 CFP) displays a behavior similar to the distribution of the COSMIC REAL sizes (REAL value), considering the granularity level of Use Cases, which graphically could be observed in Fig. 4.

Table 5. Wilcoxon post hoc test results

Comparison	Asymp. Sig. *(p-value)*	Statistical Significance >*a* =0.0125
REAL and ESB	4.8089E-30	NO
REAL and EPCU16.4	3.6339E-19	NO
REAL and EPCU44	0.281	YES
ESB and EPCU16.4	1.3091E-38	NO
ESB and EPCU44	8.7473E-50	NO
EPCU16.4 and EPCU44	8.2436E-50	NO

5 CONCLUSIONS

In this paper, using a large sample of 293 Use Cases from real projects, two approximation techniques were evaluated to identify which performs best with this dataset larger, which is larger than previous sets mentioned in related works. This implies statistically demonstrating which value distribution from the approximation techniques is more similar to REAL functional size distribution employing the standard COSMIC method, when the functional requirements are at the granularity level of Use Cases, a situation encountered very frequently in the industry.

From the previous work [13], the EPCU context appears to represent the distribution of the REAL sizes better; when the granularity level was Functional Process, 180 Functional Process were used.

From our findings related to quality criteria, it is not clear which approximation technique executes the best performance, this is because the central tendency measurements are affected by outliers, and the sample has several outliers, as in reality occurs.

It is well known that there is no standard definition for Use Case, and this could be a reason for the outliers. For instance, there are Use Cases with more than 100 or 300 CFP. The presence of outliers can be observed in Fig.s 1 - 4, even though, intuitively from the previous figures, the EPCU44 better represents the distribution of the REAL sizes. However, it is not easy to infer.

On carrying out the non-parametric test, it is possible to confirm statistically that only the distribution of the EPCU44 approximation technique displays behavior similar to that of the distribution of the COSMIC REAL sizes (REAL value), considering the granularity level of Use Cases, accepted the following hypothesis:

H: The EPCU context with an upper size cut-off at 44 CFP (EPCU44) better represents the distribution of the REAL sizes, when the granularity level of the FUR description was Use Cases.

Considering the findings and the previous work, it is possible to define when the granularity level of the FUR description was Use Cases, with our recommending the EPCU44 approximation approach, while when the granularity level of the functional user requirements description was Functional Process, the EPCU16.4 approximation approach is recommended.

The research developed in this paper only includes two of the approximation techniques mentioned in the Guideline for Early or Rapid COSMIC Functional Size Measurement [6]; others should be investigated as well, using similar experiments.

Because the spread of the use of agile practices, a similar assessment to that of this paper but employing User Histories as the granularity level of the functional user requirements description should be conducted.

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Appendix I. Data Provided by Participants for Each Use Case Identified

Table A1 shows the data provided by participants for each Functional Process identified in the experiment.

- Column 1 presents the Project identifier. For confidentially purposes, the Projects were labeled sequentially, from "Proj 1" to "Proj 4.
- Column 2 presents the Use Case identifier. For confidentially purposes, the Use Cases were labeled sequentially, from "UC 1" to "UC 293.
- Column 3 presents the functional size obtained utilizing the standard COSMIC method – in CFP units,
- Column 4 presents the value assigned for the input variable "Use Case size" for the EPCU approximation technique.
- Column 5 presents the value assigned for the input variable "Presence of objects of interest related to the Use Cases" for the EPCU approximation technique.

Table A1: Data collected by participants (project leaders)

Project ID	**UC ID**	**Use Case size (value assignment – range from 0 - 5)**	**Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)**
Proj 1	UC 1	3	2.5
Proj 1	UC 2	3	3
Proj 1	UC 3	3	3
Proj 1	UC 4	3	2.5
Proj 1	UC 5	3.5	3
Proj 1	UC 6	3	3
Proj 1	UC 7	3.5	3.5
Proj 1	UC 8	3.5	3

Project ID	**UC ID**	**Use Case size (value assignment – range from 0 - 5)**	**Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)**
Proj 1	UC 9	3.5	3
Proj 1	UC 10	3.5	3.5
Proj 1	UC 11	3.5	2.95
Proj 1	UC 12	3.5	3
Proj 1	UC 13	3.5	2.75
Proj 1	UC 14	4	2.5
Proj 1	UC 15	3.5	3.65
Proj 1	UC 16	3	4
Proj 1	UC 17	3.5	3
Proj 1	UC 18	3	3
Proj 1	UC 19	3	3
Proj 1	UC 20	3.5	3.5
Proj 1	UC 21	3.5	3.5
Proj 1	UC 22	3.5	3.5
Proj 1	UC 23	4	3.5
Proj 1	UC 24	4	3.5
Proj 1	UC 25	3.5	3.5
Proj 1	UC 26	4	3.5
Proj 1	UC 27	3.5	3.5
Proj 1	UC 28	4	3
Proj 1	UC 29	3.5	3
Proj 1	UC 30	3.5	3
Proj 1	UC 31	3.5	3

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 1	UC 32	4	3.5
Proj 1	UC 33	4	3
Proj 1	UC 34	4	3
Proj 1	UC 35	4	3.5
Proj 1	UC 36	4	3.5
Proj 1	UC 37	4	4
Proj 1	UC 38	3.85	3.5
Proj 1	UC 39	4	3.5
Proj 1	UC 40	4	3
Proj 1	UC 41	4	4
Proj 1	UC 42	4	4
Proj 1	UC 43	4	3.5
Proj 2	UC 44	2.4	1.8
Proj 2	UC 45	2.5	2.05
Proj 2	UC 46	2.85	2.4
Proj 2	UC 47	2.3	2.2
Proj 2	UC 48	3	2.6
Proj 2	UC 49	2.1	1.85
Proj 2	UC 50	2.55	2.55
Proj 2	UC 51	2.65	2.45
Proj 2	UC 52	2.35	2.8
Proj 2	UC 53	1.65	1.8
Proj 2	UC 54	2.8	2.8
Proj 2	UC 55	2.85	2.55
Proj 2	UC 56	2.3	2.1
Proj 2	UC 57	2.6	2.6
Proj 2	UC 58	1.95	1.95
Proj 2	UC 59	2.3	2.1
Proj 2	UC 60	2.65	2.1
Proj 2	UC 61	2.1	2.05
Proj 2	UC 62	3.1	2.65
Proj 2	UC 63	2.5	2.1
Proj 2	UC 64	2.6	2.25
Proj 2	UC 65	2.5	2.5
Proj 2	UC 66	2.35	2.3
Proj 2	UC 67	2.35	2.1
Proj 2	UC 68	2.35	2.35
Proj 2	UC 69	2.55	2.1
Proj 2	UC 70	2.55	2.1
Proj 2	UC 71	2.6	2.6
Proj 2	UC 72	2.5	1.4
Proj 2	UC 73	2.4	2.6
Proj 2	UC 74	1.7	1.95
Proj 2	UC 75	2.1	2.1
Proj 2	UC 76	2.3	1.95
Proj 2	UC 77	1.9	1.6
Proj 2	UC 78	2.3	2.3
Proj 2	UC 79	2.45	2.6
Proj 2	UC 80	2.35	2.15
Proj 2	UC 81	2.8	2.6
Proj 2	UC 82	2.9	2.05
Proj 2	UC 83	2.5	1.75
Proj 2	UC 84	2.1	1.95
Proj 2	UC 85	2.45	2.1
Proj 2	UC 86	3.05	1.6
Proj 2	UC 87	2.35	1.6
Proj 2	UC 88	3	3
Proj 2	UC 89	2.1	1.95
Proj 2	UC 90	1.95	1.95
Proj 2	UC 91	1.95	1.95
Proj 2	UC 92	1.8	1.6
Proj 2	UC 93	2	2.15
Proj 2	UC 94	2.3	1.95
Proj 2	UC 95	2.5	2.15
Proj 2	UC 96	2.45	2.25
Proj 2	UC 97	2.6	2.6
Proj 2	UC 98	2.5	2.55
Proj 2	UC 99	2.5	2.15
Proj 2	UC 100	3.25	2.2
Proj 2	UC 101	2.15	1.8
Proj 2	UC 102	2.25	2.05
Proj 2	UC 103	2.3	2.1
Proj 2	UC 104	2.6	1.85
Proj 2	UC 105	2.65	2.3

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 2	UC 106	2.8	1.75
Proj 2	UC 107	2.75	2.35
Proj 2	UC 108	2.7	2.55
Proj 2	UC 109	2.9	2.6
Proj 2	UC 110	2.85	2.3
Proj 2	UC 111	2.85	2.6
Proj 2	UC 112	2.75	2.55
Proj 2	UC 113	2.4	2.2
Proj 2	UC 114	2.5	1.65
Proj 2	UC 115	2.05	1.65
Proj 2	UC 116	2.5	2.5
Proj 2	UC 117	2.35	1.65
Proj 2	UC 118	2.55	2.15
Proj 2	UC 119	1.8	1.75
Proj 2	UC 120	2.3	1.8
Proj 2	UC 121	2.1	1.75
Proj 2	UC 122	2.75	1.75
Proj 2	UC 123	2.95	2.2
Proj 2	UC 124	2.75	2.25
Proj 2	UC 125	3.05	2.65
Proj 2	UC 126	2.65	1.75
Proj 2	UC 127	2.7	1.75
Proj 2	UC 128	2.5	1.75
Proj 2	UC 129	2.1	1.75
Proj 2	UC 130	1.8	1.75
Proj 2	UC 131	2.55	1.75
Proj 2	UC 132	2.8	1.75
Proj 2	UC 133	2.55	2
Proj 2	UC 134	2.35	1.75
Proj 2	UC 135	2.55	2.2
Proj 2	UC 136	2.3	1.7

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 2	UC 137	2.35	2
Proj 2	UC 138	3.25	1.75
Proj 2	UC 139	2.6	2.05
Proj 3	UC 140	3.5	3.75
Proj 3	UC 141	3.5	3
Proj 3	UC 142	3.5	2.5
Proj 3	UC 143	3.25	3.6
Proj 3	UC 144	3.3	3.4
Proj 3	UC 145	2.15	3
Proj 3	UC 146	3.6	3.9
Proj 3	UC 147	3.5	3.65
Proj 3	UC 148	2.75	3.05
Proj 3	UC 149	3.25	3.35
Proj 3	UC 150	3	4
Proj 3	UC 151	3.15	3
Proj 3	UC 152	2.55	3.8
Proj 3	UC 153	2.6	3
Proj 3	UC 154	2.55	2.5
Proj 3	UC 155	3	3.75
Proj 3	UC 156	2.25	2.75
Proj 3	UC 157	2.25	2.75
Proj 3	UC 158	3	3
Proj 3	UC 159	2.5	3.25
Proj 3	UC 160	1.5	3
Proj 3	UC 161	2.7	2.9
Proj 3	UC 162	2.45	2.5
Proj 3	UC 163	2.65	3.25
Proj 3	UC 164	1.8	2.75
Proj 3	UC 165	2.65	3.5
Proj 3	UC 166	2.85	3.75
Proj 3	UC 167	1.4	2.75
Proj 3	UC 168	3	3.5

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 3	UC 169	3	2.65
Proj 3	UC 170	3	3.5
Proj 3	UC 171	2.95	3.25
Proj 3	UC 172	3.25	3.5
Proj 3	UC 173	3.25	3.25
Proj 3	UC 174	2.95	4.25
Proj 3	UC 175	3.05	3.5
Proj 3	UC 176	2.8	2.35
Proj 3	UC 177	2.3	3
Proj 3	UC 178	2.9	2.35
Proj 3	UC 179	2.2	2.65
Proj 3	UC 180	2.55	2.35
Proj 3	UC 181	2.3	2.3
Proj 3	UC 182	2.35	2.15
Proj 3	UC 183	2.45	2.2
Proj 3	UC 184	2.35	2.5
Proj 3	UC 185	2.15	2.05
Proj 3	UC 186	2.5	3.85
Proj 3	UC 187	2.7	4
Proj 3	UC 188	2.1	3
Proj 3	UC 189	2.55	3.25
Proj 3	UC 190	2.8	3
Proj 3	UC 191	2.6	3.5
Proj 3	UC 192	3.55	3.85
Proj 3	UC 193	3.05	3.45
Proj 3	UC 194	2.8	3.35
Proj 4	UC 195	3.5	3.3
Proj 4	UC 196	3.4	3.4
Proj 4	UC 197	3	2.8
Proj 4	UC 198	3	3.1
Proj 4	UC 199	3.3	3.4
Proj 4	UC 200	3.3	3.5
Proj 4	UC 201	3.6	3
Proj 4	UC 202	3.1	2.5
Proj 4	UC 203	3.4	3
Proj 4	UC 204	3.3	3
Proj 4	UC 205	3.3	3
Proj 4	UC 206	2.6	2.5

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 4	UC 207	2.8	2.6
Proj 4	UC 208	3.4	2.8
Proj 4	UC 209	3	2.8
Proj 4	UC 210	3.2	2.2
Proj 4	UC 211	3.3	2.5
Proj 4	UC 212	2.7	2.8
Proj 4	UC 213	3.2	2.3
Proj 4	UC 214	3.2	3
Proj 4	UC 215	2.5	2.8
Proj 4	UC 216	2.8	2.4
Proj 4	UC 217	2.1	2
Proj 4	UC 218	3	2.6
Proj 4	UC 219	3.1	3
Proj 4	UC 220	2.8	3
Proj 4	UC 221	3.2	3.1
Proj 4	UC 222	1.9	2.3
Proj 4	UC 223	2.6	3
Proj 4	UC 224	3	2.5
Proj 4	UC 225	3.3	2.4
Proj 4	UC 226	3	3.1
Proj 4	UC 227	2.5	2.5
Proj 4	UC 228	3.5	2.5
Proj 4	UC 229	2.5	2.5
Proj 4	UC 230	3	3
Proj 4	UC 231	3	2.5
Proj 4	UC 232	3.2	2.5
Proj 4	UC 233	3.3	3
Proj 4	UC 234	3.2	3
Proj 4	UC 235	3.4	3.1
Proj 4	UC 236	3.2	2.5
Proj 4	UC 237	2.5	3
Proj 4	UC 238	3.9	3
Proj 4	UC 239	3.5	2.9
Proj 4	UC 240	3.2	3.4
Proj 4	UC 241	2.7	2.7
Proj 4	UC 242	3.5	3.1
Proj 4	UC 243	3	2.3

Project ID	UC ID	Use Case size (value assignment – range from 0 - 5)	Presence (level, not number) of objects of interest related to the Use Case (value assignment – range from 0 - 5)
Proj 4	UC 244	3	2.5
Proj 4	UC 245	2.5	2.5
Proj 4	UC 246	2.7	2.4
Proj 4	UC 247	3.3	3
Proj 4	UC 248	2.7	2
Proj 4	UC 249	3.8	3.5
Proj 4	UC 250	3.3	3.1
Proj 4	UC 251	3.1	2.5
Proj 4	UC 252	2.8	2.8
Proj 4	UC 253	3.6	3.5
Proj 4	UC 254	2.5	2.6
Proj 4	UC 255	2.9	2.6
Proj 4	UC 256	3.3	2.5
Proj 4	UC 257	2.6	2
Proj 4	UC 258	3.2	2.4
Proj 4	UC 259	2.5	2.3
Proj 4	UC 260	2.5	2.2
Proj 4	UC 261	3	2.9
Proj 4	UC 262	2.7	3
Proj 4	UC 263	2.7	2.8
Proj 4	UC 264	3.2	3
Proj 4	UC 265	2.5	2.2
Proj 4	UC 266	2.5	2.2
Proj 4	UC 267	3.8	3
Proj 4	UC 268	3.4	2.8
Proj 4	UC 269	3.6	3
Proj 4	UC 270	3.6	3.5
Proj 4	UC 271	3.2	2.7
Proj 4	UC 272	2.4	2.9
Proj 4	UC 273	2.5	1.8
Proj 4	UC 274	2.7	2.7
Proj 4	UC 275	2.7	2.7
Proj 4	UC 276	2	2.5
Proj 4	UC 277	3	2.6
Proj 4	UC 278	3.1	2.6
Proj 4	UC 279	3.2	1.8
Proj 4	UC 280	3	3
Proj 4	UC 281	3.2	2.8
Proj 4	UC 282	3	2.5
Proj 4	UC 283	2	2
Proj 4	UC 284	3.3	2.4
Proj 4	UC 285	3	2.9
Proj 4	UC 286	3	2.3
Proj 4	UC 287	2.5	1.8
Proj 4	UC 288	3	2.5
Proj 4	UC 289	2.5	2
Proj 4	UC 290	3.3	2.6
Proj 4	UC 291	3.9	2
Proj 4	UC 292	2	2
Proj 4	UC 293	2.5	2.5

Appendix II. COSMIC Functional Size and Approximation

COSMIC functional size and approximation for each Functional Process are presented in Table A2 II where:

- Column 1 presents the Project identifier. For purposes of confidentiality , the Projects were labeled sequentially, from “Proj 1” to “Proj 4,
- Column 2 presents the Use Case identifier. For purposes of confidentiality, the Use Cases were labeled sequentially, from “UC 1” to “UC 293,
- Column 3 presents the functional size obtained utilizing the standard COSMIC method – in CFP units,
- Column 4 presents the Equal Size Bands approximation approach,
- Column 5 presents the EPCU size approximation approach using an output variable domain function from 2 - 16.4 CFP [9] [10], and
- Column 6 presents the EPCU size approximation approach using an output variable domain function from 2 - 44 CFP [11].

Table A2: Functional size – Real and from 3 approximation techniques

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
1	UC 1	9	7.7	9.84	14.60
1	UC 2	9	7.7	12.72	27.52
1	UC 3	9	7.7	12.72	27.52
1	UC 4	22	7.7	9.84	14.60
1	UC 5	132	10.7	12.56	26.78
1	UC 6	9	7.7	12.72	27.52
1	UC 7	4	10.7	14.72	36.49
1	UC 8	343	10.7	12.56	26.78
1	UC 9	11	10.7	12.56	26.78
1	UC 10	8	10.7	14.72	36.49
1	UC 11	20	10.7	12.56	26.78
1	UC 12	8	10.7	12.56	26.78
1	UC 13	6	10.7	11.71	22.96
1	UC 14	154	10.7	9.84	14.60
1	UC 15	12	10.7	15.98	42.11
1	UC 16	9	7.7	16.40	44.00
1	UC 17	37	10.7	12.56	26.78
1	UC 18	75	7.7	12.72	27.52
1	UC 19	13	7.7	12.72	27.52
1	UC 20	9	10.7	14.72	36.49
1	UC 21	26	10.7	14.72	36.49
1	UC 22	132	10.7	14.72	36.49
1	UC 23	14	10.7	15.09	38.12
1	UC 24	9	10.7	15.09	38.12
1	UC 25	37	10.7	14.72	36.49
1	UC 26	49	10.7	15.09	38.12
1	UC 27	11	10.7	14.72	36.49
1	UC 28	9	10.7	12.46	26.36
1	UC 29	22	10.7	12.56	26.78

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
1	UC 30	16	10.7	12.56	26.78
1	UC 31	8	10.7	12.56	26.78
1	UC 32	8	10.7	15.09	38.12
1	UC 33	21	10.7	12.46	26.36
1	UC 34	19	10.7	12.46	26.36
1	UC 35	32	10.7	15.09	38.12
1	UC 36	5	10.7	15.09	38.12
1	UC 37	46	10.7	16.40	44.00
1	UC 38	17	10.7	15.09	38.12
1	UC 39	11	10.7	15.09	38.12
1	UC 40	15	10.7	12.46	26.36
1	UC 41	15	10.7	16.40	44.00
1	UC 42	16	10.7	16.40	44.00
1	UC 43	10	10.7	15.09	38.12
2	UC 44	4	7.7	7.53	10.05
2	UC 45	27	7.7	8.79	12.39
2	UC 46	31	7.7	9.41	13.70
2	UC 47	39	7.7	7.97	11.24
2	UC 48	37	7.7	10.73	18.59
2	UC 49	8	7.7	6.65	8.86
2	UC 50	6	7.7	10.56	17.81
2	UC 51	20	7.7	9.84	14.60
2	UC 52	47	7.7	11.05	20.60
2	UC 53	20	4.8	5.50	7.09
2	UC 54	12	7.7	11.80	23.38
2	UC 55	23	7.7	10.70	18.45
2	UC 56	32	7.7	7.76	10.81
2	UC 57	32	7.7	10.56	17.81
2	UC 58	11	4.8	6.56	8.80
2	UC 59	35	7.7	7.76	10.81
2	UC 60	59	7.7	8.73	12.26
2	UC 61	23	7.7	7.01	9.60
2	UC 62	39	10.7	11.43	21.72
2	UC 63	52	7.7	8.79	12.39
2	UC 64	9	7.7	9.27	13.39
2	UC 65	9	7.7	9.84	14.60
2	UC 66	6	7.7	8.71	12.53
2	UC 67	8	7.7	8.25	11.56
2	UC 68	17	7.7	8.92	12.97
2	UC 69	9	7.7	8.77	12.36
2	UC 70	19	7.7	8.77	12.36
2	UC 71	10	7.7	10.56	17.81
2	UC 72	12	7.7	6.95	8.53
2	UC 73	19	7.7	10.08	16.26
2	UC 74	17	4.8	6.02	7.74
2	UC 75	9	7.7	7.01	9.60
2	UC 76	12	7.7	7.55	10.36
2	UC 77	20	4.8	5.49	6.98
2	UC 78	13	7.7	8.16	11.64
2	UC 79	15	7.7	10.36	16.95
2	UC 80	22	7.7	8.48	12.05
2	UC 81	37	7.7	10.66	18.25
2	UC 82	19	7.7	8.61	12.01
2	UC 83	14	7.7	8.00	10.74
2	UC 84	9	7.7	6.83	9.24
2	UC 85	7	7.7	8.79	12.39
2	UC 86	5	10.7	7.74	10.18
2	UC 87	14	7.7	7.04	9.03
2	UC 88	8	7.7	12.72	27.52
2	UC 89	31	7.7	6.83	9.24
2	UC 90	21	4.8	6.56	8.80
2	UC 91	11	4.8	6.56	8.80
2	UC 92	4	4.8	5.21	6.63
2	UC 93	27	4.8	7.16	9.76
2	UC 94	31	7.7	7.55	10.36
2	UC 95	39	7.7	9.05	12.94
2	UC 96	37	7.7	9.32	13.50
2	UC 97	8	7.7	10.56	17.81
2	UC 98	6	7.7	10.36	16.95
2	UC 99	20	7.7	9.05	12.94
2	UC 100	47	10.7	8.80	12.42
2	UC 101	20	7.7	6.76	8.93
2	UC 102	23	7.7	7.76	10.81
2	UC 103	32	7.7	7.76	10.81

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
2	UC 104	32	7.7	8.26	11.28
2	UC 105	35	7.7	9.15	13.16
2	UC 106	59	7.7	8.04	10.81
2	UC 107	23	7.7	9.43	13.74
2	UC 108	39	7.7	10.61	18.04
2	UC 109	52	7.7	10.70	18.45
2	UC 110	9	7.7	9.08	13.00
2	UC 111	9	7.7	10.70	18.45
2	UC 112	6	7.7	10.66	18.25
2	UC 113	8	7.7	8.48	12.05
2	UC 114	17	7.7	7.74	10.18
2	UC 115	9	7.7	6.28	8.09
2	UC 116	19	7.7	9.84	14.60
2	UC 117	10	7.7	7.29	9.54
2	UC 118	12	7.7	9.02	12.88
2	UC 119	19	4.8	5.75	7.48
2	UC 120	17	7.7	7.11	9.45
2	UC 121	9	7.7	6.47	8.48
2	UC 122	12	7.7	8.04	10.81
2	UC 123	20	7.7	8.79	12.39
2	UC 124	13	7.7	9.11	13.07
2	UC 125	15	10.7	11.43	21.72
2	UC 126	19	7.7	8.02	10.77
2	UC 127	22	7.7	8.02	10.77
2	UC 128	37	7.7	8.00	10.74
2	UC 129	9	7.7	6.47	8.48
2	UC 130	14	4.8	5.75	7.48
2	UC 131	7	7.7	8.01	10.75
2	UC 132	5	7.7	8.04	10.81
2	UC 133	8	7.7	8.52	11.82
2	UC 134	14	7.7	7.53	10.05
2	UC 135	31	7.7	9.02	12.88
2	UC 136	21	7.7	6.89	8.98
2	UC 137	11	7.7	8.01	11.06
2	UC 138	12	10.7	8.07	10.88
2	UC 139	15	7.7	8.77	12.36
3	UC 140	121	10.7	16.40	44.00
3	UC 141	8	10.7	12.56	26.78
3	UC 142	15	10.7	9.84	14.60
3	UC 143	5	10.7	15.17	38.48
3	UC 144	124	10.7	14.10	33.70
3	UC 145	13	7.7	11.27	22.46
3	UC 146	132	10.7	16.40	44.00
3	UC 147	153	10.7	15.98	42.11
3	UC 148	22	7.7	13.01	28.82
3	UC 149	22	10.7	14.10	33.70
3	UC 150	22	7.7	16.40	44.00
3	UC 151	6	10.7	12.74	27.61

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
3	UC 152	103	7.7	16.40	44.00
3	UC 153	29	7.7	12.48	26.44
3	UC 154	17	7.7	9.84	14.60
3	UC 155	13	7.7	16.40	44.00
3	UC 156	20	7.7	10.73	19.66
3	UC 157	13	7.7	10.73	19.66
3	UC 158	15	7.7	12.72	27.52
3	UC 159	11	7.7	14.04	33.42
3	UC 160	15	4.8	9.31	16.00
3	UC 161	10	7.7	12.06	24.56
3	UC 162	54	7.7	9.84	14.60
3	UC 163	9	7.7	13.95	33.01
3	UC 164	40	4.8	9.64	17.05
3	UC 165	35	7.7	14.83	36.98
3	UC 166	23	7.7	16.40	44.00
3	UC 167	15	4.8	8.35	13.11
3	UC 168	47	7.7	14.55	35.72
3	UC 169	11	7.7	11.41	21.62
3	UC 170	26	7.7	14.55	35.72
3	UC 171	31	7.7	13.69	31.83
3	UC 172	15	10.7	14.58	35.82
3	UC 173	29	10.7	13.71	31.96

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
3	UC 174	23	7.7	16.40	44.00
3	UC 175	30	10.7	14.53	35.60
3	UC 176	39	7.7	9.43	13.74
3	UC 177	16	7.7	11.62	23.62
3	UC 178	19	7.7	9.41	13.70
3	UC 179	17	7.7	10.06	17.19
3	UC 180	5	7.7	9.48	13.85
3	UC 181	2	7.70	8.16	11.64
3	UC 182	5	7.70	8.48	12.05
3	UC 183	82	7.70	9.05	12.94
3	UC 184	62	7.70	9.58	14.05
3	UC 185	29	7.70	7.36	10.15
3	UC 186	40	7.70	16.40	44.00
3	UC 187	41	7.70	16.40	44.00
3	UC 188	21	7.70	10.96	21.42
3	UC 189	14	7.70	14.01	33.31
3	UC 190	36	7.70	12.59	26.93
3	UC 191	36	7.70	15.01	37.79
3	UC 192	12	10.70	16.40	44.00
3	UC 193	55	10.70	14.53	35.60
3	UC 194	18	7.70	14.25	34.39
4	UC 195	37	10.70	13.90	32.81

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
4	UC 196	33	10.70	14.18	34.04
4	UC 197	9	7.70	11.94	24.01
4	UC 198	31	7.70	13.04	28.94
4	UC 199	32	10.70	14.10	33.70
4	UC 200	49	10.70	14.58	35.82
4	UC 201	64	10.70	12.50	26.53
4	UC 202	10	10.70	9.84	14.60
4	UC 203	18	10.70	12.62	27.08
4	UC 204	15	10.70	12.69	27.38
4	UC 205	31	10.70	12.69	27.38
4	UC 206	20	7.70	9.84	14.60
4	UC 207	13	7.70	10.66	18.25
4	UC 208	42	10.70	11.84	23.57
4	UC 209	64	7.70	11.94	24.01
4	UC 210	50	10.70	8.78	12.37
4	UC 211	24	10.70	9.84	14.60
4	UC 212	17	7.70	11.62	22.56
4	UC 213	7	10.70	9.05	12.94
4	UC 214	3	10.70	12.74	27.61
4	UC 215	3	7.70	11.41	21.66
4	UC 216	6	7.70	9.43	13.74
4	UC 217	7	7.70	6.83	9.24
4	UC 218	2	7.70	10.73	18.59
4	UC 219	23	10.70	12.75	27.66
4	UC 220	78	7.70	12.59	26.93
4	UC 221	35	10.70	13.05	28.97
4	UC 222	17	4.80	7.33	9.91
4	UC 223	83	7.70	12.48	26.44
4	UC 224	12	7.70	9.84	14.60
4	UC 225	5	10.70	9.40	13.68
4	UC 226	8	7.70	13.04	28.94
4	UC 227	6	7.70	9.84	14.60
4	UC 228	91	10.70	9.84	14.60
4	UC 229	26	7.70	9.84	14.60
4	UC 230	22	7.70	12.72	27.52
4	UC 231	158	7.70	9.84	14.60
4	UC 232	7	10.70	9.84	14.60
4	UC 233	21	10.70	12.69	27.38
4	UC 234	3	10.70	12.74	27.61
4	UC 235	15	10.70	13.02	28.85
4	UC 236	6	10.70	9.84	14.60
4	UC 237	4	7.70	12.46	26.36
4	UC 238	24	10.70	12.46	26.36
4	UC 239	5	10.70	12.12	24.81
4	UC 240	13	10.70	14.06	33.49
4	UC 241	11	7.70	11.21	20.75
4	UC 242	11	10.70	13.01	28.79
4	UC 243	4	7.70	9.06	12.95

Project ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
4	UC 244	39	7.70	9.84	14.60
4	UC 245	18	7.70	9.84	14.60
4	UC 246	26	7.70	9.46	13.79
4	UC 247	8	10.70	12.69	27.38
4	UC 248	8	7.70	8.50	11.77
4	UC 249	23	10.70	15.09	38.12
4	UC 250	4	10.70	13.03	28.91
4	UC 251	16	10.70	9.84	14.60
4	UC 252	32	7.70	11.80	23.38
4	UC 253	45	10.70	14.93	37.42
4	UC 254	7	7.70	10.36	16.95
4	UC 255	21	7.70	10.70	18.45
4	UC 256	27	10.70	9.84	14.60
4	UC 257	15	7.70	8.52	11.82
4	UC 258	14	10.70	9.39	13.65
4	UC 259	6	7.70	9.32	13.50
4	UC 260	14	7.70	9.05	12.94
4	UC 261	3	7.70	12.37	25.94
4	UC 262	7	7.70	12.53	26.64
4	UC 263	3	7.70	11.62	22.56
4	UC 264	15	10.70	12.74	27.61
4	UC 265	2	7.70	9.05	12.94
4	UC 266	4	7.70	9.05	12.94
4	UC 267	14	10.70	12.46	26.36
4	UC 268	13	10.70	11.84	23.57
4	UC 269	16	10.70	12.50	26.53
4	UC 270	14	10.70	14.93	37.42
4	UC 271	16	10.70	11.42	21.69
4	UC 272	15	7.70	11.53	22.76
4	UC 273	16	7.70	8.00	10.74
4	UC 274	6	7.70	11.21	20.75
4	UC 275	5	7.70	11.21	20.75
4	UC 276	6	4.80	8.53	11.84
4	UC 277	3	7.70	10.73	18.59
4	UC 278	3	10.70	10.74	18.65
4	UC 279	28	10.70	8.09	10.92
4	UC 280	6	7.70	12.72	27.52
4	UC 281	6	10.70	11.96	24.09
4	UC 282	9	7.70	9.84	14.60
4	UC 283	3	4.80	6.56	8.80
4	UC 284	19	10.70	9.40	13.68
4	UC 285	7	7.70	12.37	25.94

Pro-ject ID	UC ID	REAL	ESB	EPCU16.4	EPCU44
4	UC 286	6	7.70	9.06	12.95
4	UC 287	22	7.70	8.00	10.74
4	UC 288	3	7.70	9.84	14.60
4	UC 289	60	7.70	8.53	11.84
4	UC 290	16	10.70	10.72	18.53
4	UC 291	2	10.70	8.53	11.84
4	UC 292	108	4.80	6.56	8.80
4	UC 293	4	7.70	9.84	14.60

Appendix III. Friedman Test Results from SPSS®

Descriptive Statistics

	N	Mean	Std. Deviation	Minimun	Maximun
REAL	293	24.7406	31.84897	0.00	343.00
ESB	293	8.5556	1.68440	4.80	10.70
EPCU16	293	10.8944	2.76991	5.21	16.40
EPCU44	293	21.0759	10.40606	6.63	44.00

Ranks

	Mean Rank
REAL	2.89
ESB	1.35
EPCU16	2.20
EPCU44	3.55

Tests Statistics[a]

N	293
Chi-Square	468.936
df	3
Asymp. Sig.	2.57215388100136E-101

Appendix IV. Wilcoxon Test Results from SPSS®

ESB – REAL

		N	Mean Rank	Sum of Ranks
ESB - REAL	Negative Ranks	230[a]	165.49	38063.00
	Positive Ranks	63[b]	79.49	5008.00
	Ties	0[c]		
	Total	293		

a. ESB < REAL

b. ESB > REAL

c. ESB = REAL

Test Statistics[a]

	ESB - REAL
Z	-11.388[b]
Asymp. Sig. (2-tailed)	4.8089036753386E-30

a. Wilcoxon Test with sign
b. Based in negative ranks.

EPCU16 - REAL

Ranks

		N	Mean Rank	Sum of Ranks
EPCU16 - REAL	Negative Ranks	194[a]	177.95	34523.00
	Positive Ranks	99[b]	86.34	8548.00
	Ties	0[c]		
	Total	293		

a. EPCU16 < REAL

b. EPCU16 > REAL

c. EPCU16 = REAL

Test Statistics[a]

	EPCU16 - REAL
Z	-8.948[b]
Asymp. Sig. (2-tailed)	3.6339E-19

a. Wilcoxon Test with sign

b. Based in positive ranks.

EPCU44 – REAL

Ranks

		N	Mean Rank	Sum of Ranks
EPCU44 - REAL	Negative Ranks	130[a]	153.62	19971.00
	Positive Ranks	163[b]	141.72	23100.00
	Ties	0[c]		
	Total	293		

a. EPCU44 < REAL

b. EPCU44 > REAL

c. EPCU44 = REAL

Test Statistics[a]

	EPCU44 - REAL
Z	-1.078[b]
Asymp. Sig. (2-tailed)	.281

a. Wilcoxon Test with sign

b. Based in positive ranks.

EPCU44 – ESB

Ranks

		N	Mean Rank	Sum of Ranks
EPCU44 - ESB	Negative Ranks	1[a]	4.00	4.00
	Positive Ranks	292[b]	147.49	43067.00
	Ties	0[c]		
	Total	293		

a. EPCU44 < ESB

b. EPCU44 > ESB

c. EPCU44 = ESB

Tests Statistics[a]

	MRE_EPCU44 - ESB
Z	-14.835[b]
Asymp. Sig. (2-tailed)	8.7473E-50

a. Wilcoxon Test with sign

b. Based in positive ranks.

EPCU16 – ESB

Ranks

		N	Mean Rank	Sum of Ranks
EPCU16 - ESB	Negative Ranks	39[a]	68.58	2674.50
	Positive Ranks	254[b]	159.04	40396.50
	Ties	0[c]		
	Total	293		

a. EPCU16 < ESB

b. EPCU16 > ESB

c. EPCU16 = ESB

Test Statistics[a]

	MRE_EPCU16 - ESB
Z	-12.995[b]
Asymp. Sig. (2-tailed)	1.3091E-38

a. Wilcoxon Test with sign

b. Based in positive ranks.

EPCU16 - EPCU44

Ranks

		N	Mean Rank	Sum of Ranks
EPCU16 - EPCU44	Negative Ranks	0[a]	0.00	0.00
	Positive Ranks	293[b]	147.00	43071.00
	Ties	0[c]		
	Total	293		

a. EPCU16 < EPCU44

b. EPCU16 > EPCU44

c. EPCU16 = EPCU44

Test Statistics[a]

	MRE_EPCU16 - MRE_EPCU44
Z	-14.839[b]
Asymp. Sig. (2-tailed)	8.2436E-50