Web Effort Estimation: Function Points Analysis vs. COSMIC

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Abstract

Context: Software development effort estimation is a crucial management task that critically depends on the adopted size measure. Several Functional Size Measurement (FSM) methods have been proposed. COSMIC is considered a 2^{nd} generation FSM method, to differentiate it from Function Point Analysis (FPA) and its variants, considered as 1^{st} generation ones. In the context of Web applications, few investigations have been performed to compare the effectiveness of the two generations. Software companies could benefit from this analysis to evaluate if it is worth to migrate from a 1^{st} generation method to a 2^{nd} one.
Objective: The main goal of the paper is to empirically investigate if COSMIC is more effective than FPA for Web effort estimation. Since software companies using FPA cannot build an estimation model based on COSMIC as long as they do not have enough COSMIC data, the second goal of the paper is to investigate if conversion equations can be exploited to support the migration from FPA to COSMIC.
Method: Two empirical studies have been carried out by employing an industrial data set. The first one compared the effort prediction accuracy obtained with Function Points (FPs) and COSMIC, using two estimation

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techniques (Simple Linear Regression and Case-Based Reasoning). The second study assessed the effectiveness of a two-step strategy that first exploits a conversion equation to transform historical FPs data into COSMIC, and then builds a new prediction model based on those estimated COSMIC sizes.
Results: The first study revealed that, on our data set, COSMIC was significantly more accurate than FPs in estimating the development effort. The second study revealed that the effectiveness of the analyzed two-step process critically depends on the employed conversion equation.
Conclusion: For Web effort estimation COSMIC can be significantly more effective than FPA. Nevertheless, additional research must be conducted to identify suitable conversion equations so that the two-step strategy can be effectively employed for a smooth migration from FPA to COSMIC.

Keywords: Web effort estimation; Functional Size measures; COSMIC; IFPUG Function Point Analysis

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1. Introduction

A crucial task for software project management is to accurately estimate the effort required to develop an application, since this estimate is usually a key factor for making a bid, planning the development activities, allocating resources adequately, and so on. Indeed, development effort, meant as the work carried out by software practitioners, is the dominant project cost, being also the most difficult to estimate and control. Significant over- or under-estimates can be very expensive and deleterious for the competitiveness of a software company [1].

FSM methods are meant to measure the software size by quantifying the "functionality" provided to the users. In particular, the Function Point Analysis (FPA) was the first FSM method, defined in 1979 [2]. Since then, several variants have been proposed (e.g., MarkII and NESMA) with the aim of improving the size measurement or extending the applicability domains [3]. As a consequence, FSM methods are nowadays widely applied in the industrial field for sizing software systems and then using the obtained functional size as independent variable in estimation models. It is worth noting that all the above methods fall in the 1^{st} generation of FSM methods, distinguishing them from COSMIC, which is considered a 2^{nd} generation FSM method, due to several specific characteristics. In particular, COSMIC was the first FSM approach conceived to comply to the standard ISO/IEC14143/1 [4]. It is based on fundamental principles of software engineering and measurement theory, and it was developed to be suitable for a broader range of application domains [5].

In the context of Web applications, few investigations have been performed to analyze and assess the use of FPA (e.g., [6][7][8]). A few studies have also been carried out on the use of COSMIC for sizing Web applications and estimating development effort [9][10][11][12][13]. However, no study compared the effectiveness of using COSMIC with respect to the use of FPA for Web effort estimation. Moreover, only few studies were based on industrial experiences, also due to the lack of suitable data sets including information about both COSMIC and FPA sizes, and effort data. Thus, there is the need for more empirical studies in this context that can support software companies in the choice of one of these measurement methods. A possible empirical evidence that COSMIC is more effective than FPA for effort estimation could motivate those software companies that usually employ FPA to migrate to COSMIC. It is evident that the migration from the 1^{st} generation measurement methods to the 2^{nd} generation requires some additional costs. Indeed, not only it is necessary to acquire new expertise within the company, but there is also the need to compute again the size of the applications measured in the past with FPA, in order to use them to build new effort estimation models based on COSMIC [14][15] or for other purposes (e.g., productivity benchmarking).

These issues motivated our investigation. Thus, the main aim of this work is to assess whether COSMIC is more effective than FPA for the effort estimation of Web applications. To this end, we investigated the following research question:

$RQ1_a$ Is the COSMIC measure significantly better than FPs for estimating Web application development effort by using Simple Linear Regression and Case Based Reasoning?

In the case we have indications that size in terms of COSMIC is more informative than the size in terms of FPs, it would be interesting to highlight which characteristics contribute more in such information [16]. Since for each application we have data about the Base Functional Components (BFCs) that give cumulatively the COSMIC size and FP sizes, we employed them to investigate which BFCs are more informative for predicting the effort. To this end, we investigated the following research question:

$RQ1_b$ Which COSMIC and FP BFCs are significant in estimating Web application development effort?

To answer $RQ1_a$ and $RQ1_b$ we performed an empirical study using data from 25 industrial Web applications. In particular, for $RQ1_a$ we employed two widely and successfully used techniques [17] for building effort estimation models, namely Simple Linear Regression (SLR), that is a model-based approach, and Case-Based Reasoning (CBR), that is a Machine Learning-based solution, for predicting the development effort[1]. On the other hand, to answer $RQ1_b$, we verified the correlation between each BFC and the effort and we have analyzed the distribution of the BFCs with respect to the final size.

A positive answer to the first research question might motivate software companies to migrate from FPA to COSMIC for sizing new Web applications, but also raises the question on how to manage such a transition. Indeed, a company would be interested in how to start using COSMIC for effort estimation having only an internal database of past project measured with FPA, thus without any suitable estimation model for the new measure. The simplest strategy to estimate the effort of new applications, until there is not enough historical data based on COSMIC, is to remeasure the past projects with this method, but this requires a lot of time and effort and in soma cases it cannot be possible due to the lack of appropriate information. Another solution could be to exploit a (linear or non-linear) conversion equation proposed in the literature to obtain COSMIC sizes from the old FPs ones [14]. This allows the company to exploit its historical FPs data using a two-step estimation process (2SEP from here on) for building effort estimation models as shown in Figure 1. In more details, the first step consists of applying a conversion equation to each project in the historical data set, to get an estimated COSMIC size starting from the FP one. This gives to the software company a new historical data set based on the estimated COSMIC. In the second step, it is possible to exploit this data set and SLR (or another estimation technique) to build a COSMIC based effort estimation model. This model can be used to predict the effort of the new applications, now sized

[1]Notice that we did not take into account other estimation methods, e.g., Support Vector Regression [18] [19], Search-based approaches [20], and Web-COBRA [10], or combination of techniques, e.g., [21], since our focus was to compare FSM methods rather than specific techniques.

with COSMIC.

We are aware of the possibility that effort estimations based on estimated sizes can be less accurate than the ones based on measured sizes. A company would be interested in using 2SEP for a smooth migration if the obtained effort predictions have an accuracy at least not significantly worse than that obtained still using FPA. So, to analyze the effectiveness of 2SEP we investigated the following research question:

- $RQ2_a$ Is the Web effort estimation accuracy obtained employing 2SEP, with (linear and non-linear) *external* conversion equations, not significantly worse than the accuracy achieved by exploiting FPs in models built with SLR?

It is worth noting that another strategy for a software company could be to remeasure a sample of projects with COSMIC and use that subset to build an internal conversion equation that can be exploited in the first step of 2SEP to get an estimated COSMIC size for all the other projects of the historical data set. Nevertheless, this approach requires the extra effort to remeasure in terms of COSMIC at least a sample of projects. In the present paper we investigated also the effectiveness of 2SEP using conversion equations built on a sample of the 25 projects by analyzing how good was effort estimation using such company-specific equations. To this end, we investigated the following research question:

- $RQ2_b$ Is the Web effort estimation accuracy obtained employing 2SEP, with (linear and non-linear) *internal* conversion equations, not significantly worse than the accuracy achieved by exploiting FPs in models built with SLR?

To answer $RQ2_a$ and $RQ2_b$ we performed a second empirical study employing the same data set of 25 Web applications used in the first one, some external conversion equations and the internal conversion equations built considering a small sample of Web applications. To the best of our knowledge, the previous studies (e.g., [14] [22] [23]) investigating the conversion from FPs to COSMIC sizes focused only on showing that it is possible to build conversion equations, while the present study is the first that assesses the effectiveness of the sizes obtained using some conversion equations for effort estimation purposes.

The remainder of the paper is organized as follows. In Section 2 we briefly describe the FSM methods employed in our study, namely FPA and

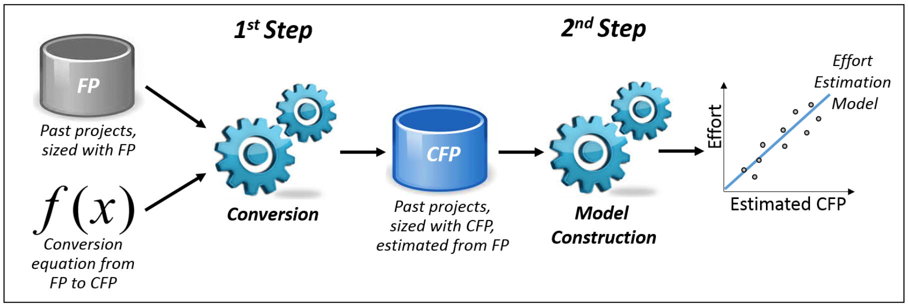


Figure 1: The two-step process for building effort estimation models (2SEP).

COSMIC, and then we present related work on the use of FPA and COSMIC for Web effort estimation. In Sections 3 and 4 we present the two performed empirical studies. Threats to validity of both empirical studies are discussed in Section 5, while Section 6 concludes the paper giving some final remarks.

2. Background

In the following, we provide a brief history of FSM methods and recall the main notions of FPA and COSMIC.

2.1. A brief history of FSM methods

Software size measures can be grouped in two main families: the *Functional* and *Dimensional* ones. A Functional Size Measure is defined as "a size of software derived by quantifying the Functional User Requirements (FURs)" [4]. Thus, FSMs are particularly suitable to be applied in the early phases of the development lifecycle, when only FURs are available, being the typical choice for tasks such as estimating a project development effort. Moreover, they are independent from the adopted technologies, allowing comparisons among projects developed with different platforms, solutions, and so on. Dimensional sizes basically count some structural properties of a software artifact, such as LOCs, number of Web pages, and so on. They can be applied only after the artifact has been developed, they are strongly dependent on the adopted technological solutions, and often a standard counting procedure is missing [24, 25]. The first FSM method proposed in the literature was the FPA, introduced by Albrecht in 1979 [2] as a measure (the Function Points) to overcome the limitations of LOCs, by quantifying the "'functionality"' provided by a software, from the end-user point of view. Indeed, FPA can be seen as a structured method to perform a functional decomposition of the system. In this way, its size can be considered as the (weighted) sum of unitary elements (its FURs), that can be measured more easily than the whole system. FPA has evolved in many different ways. The original formulation was extended by Albrecht and Gaffney [26]. Then, since 1986 FPA is managed by the International Function Point Users Group (IFPUG) [27] and it is named IFPUG FPA (IFPUG, for short), which has been standardized by ISO as ISO/IEC 20926:2009. Nevertheless, since FPA was designed from the experience gained by Albrecht on the development of Management Information Systems, the applicability of this method to other software domains has been highly debated (e.g., [28, 29]). As a consequence, many variants of FPA were defined for specific domains, such as MkII Function Point for data-rich business applications, or Full Function Point (FFP) method for embedded and control systems [3]. Since these methods are all based on the original formulation by Albrecht, they are also known as 1^{st} generation FSM methods.

In the middle of the 90's, some researchers highlighted important issues in the foundations of FPA against the measurement theory. Indeed, in many steps of the FPA process an improper use of different types of scales was highlighted. Moreover, how the "'weights"' were defined and used in the method has been object of discussion in the literature (e.g., [30, 31]).

To overcome these issues, and also to define a broader measurement framework able to tackle new IT challenges, at the end of the 90's a group of experienced software measurers formed the Common Software Measurement International Consortium (COSMIC), whose result was the COSMIC-FFP method, which is considered the first "2^{nd} generation FSM method". To highlight this concept, the first version of the method was the 2.0. Many important refinements were introduced in 2007 in the version 3.0, named simply COSMIC, and standardized as ISO/IEC 19761:2011. The current version of COSMIC is 4.0.1, introduced in April 2015.

In the following we describe the main concepts underlying the IFPUG and the COSMIC methods. Among the 1^{st} generation methods, we analyze IFPUG since it is the most widely used by software practitioners.

2.2. The IFPUG method

IFPUG sizes an application starting from its FURs (or by other software artifacts that can be abstracted in terms of FURs).

In particular, to identify the set of "features" provided by the software, each FUR is functionally decomposed into Base Functional Components (BFC), and each BFC is categorized into one of five Data or Transactional BFC Types. The Data functions can be defined as follows:

- Internal Logical Files (ILF) are logical, persistent entities maintained by the application to store information of interest.

- External Interface Files (EIF) are logical, persistent entities that are referenced by the application, but are maintained by another software application.

The Transactional ones are defined as follows:

- External Inputs (EI) are logical, elementary business processes that cross into the application boundary to maintain the data on an Internal Logical File.

- External Outputs (EO) are logical, elementary business processes that result in data leaving the application boundary to meet a user requirements (e.g., reports, screens).

- External Inquires (EQ) are logical, elementary business processes that consist of a data trigger followed by a retrieval of data that leaves the application boundary (e.g., browsing of data).

Once the BFCs have been identified, the "complexity" of each BFC is assessed. This step depends on the kind of function type and requires the identification of further attributes (such as the number of data fields to be processed). Once derived this information, a table provided in the IFPUG method [27] specifies the complexity of each function, in terms of Unadjusted Function Points (UFP).

The sum of all these UFPs gives the functional size of the application. Subsequently, a Value Adjustment Factor (VAF) can be computed to take into account some non-functional requirements, such as Performances, Reusability, and so on. The final size of the application in terms of Function Points is given by $FP = UFP \cdot VAF$.

For more details about the application of the IFPUG method, readers may refer to the counting manual [27].

2.3. The COSMIC method

The basic idea underlying the COSMIC method is that, for many types of software, most of the development efforts are devoted to handle data movements from/to persistent storage and users. Thus, the number of these data movements can provide a meaningful sight of the system size [5]. As a consequence, the measurement process consists of three phases:

1. The *Measurement Strategy* phase is meant to define the *purpose* of the measurement, the *scope* (i.e. the set of FURs to be included in the measurement), the *functional users* of each piece of software (i.e. the senders and intended recipients of data to/from the software to be measured), and the *level of granularity* of the available artifacts.
2. The *Mapping Phase* is a crucial process to express each FUR in the form required by the *COSMIC Generic Software Model*. This model, necessary to identify the key elements of a FUR to be measured , assumes that (I) each FUR can be mapped into a unique functional process, meant as a cohesive and independently executable set of data movements, (II) each functional process consists of sub-processes, and (III) each sub-process may be either a data movement or a data manipulation. To measure these data movements, three other concepts have to be identified. A *Triggering Event* is an action of a functional user of the piece of software triggering one or more functional processes. A *Data Group* is a distinct, non-empty and non-ordered set of data attributes, where each attribute describes a complementary aspect of the same object of interest. A *Data Attribute* is the smallest piece of information, within an identified data group, carrying a meaning from the perspective of the interested FUR. As depicted in Figure 2, data movements are defined as follows:
    - An Entry (E) moves a data group from a functional user across the boundary into the functional process where it is required.
    - An Exit (X) moves a data group from a functional process across the boundary to the functional user that requires it.
    - A Read (R) moves a data group from persistent storage within each of the functional process that requires it.
    - A Write (W) moves a data group lying inside a functional process to persistent storage.

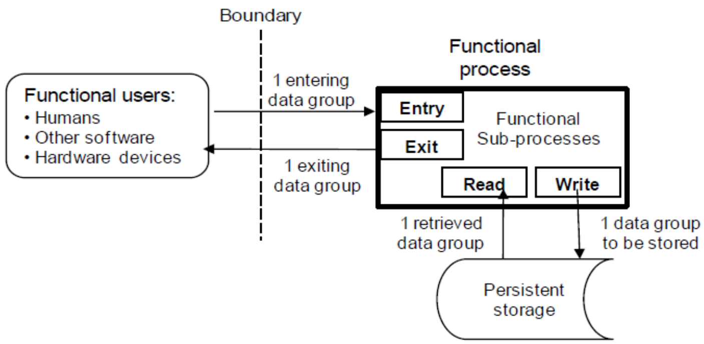


Figure 2: The four types of Data Movements, and their relationship with a Functional Process [5]

3. The *Measurement Phase*, where the data movements of each functional process have to be identified and counted. Each of them is counted as 1 COSMIC Function Point (CFP) that is the COSMIC measurement unit. Thus, the size of an application within a defined scope is obtained by summing the sizes of all the functional processes within the scope.

For more details about the COSMIC method, readers are referred to the COSMIC Measurement Manual [5].

2.4. Related work

In the literature there is a number of studies on the assessment of FPA and COSMIC methods for effort estimation. However, very few of them investigate their effectiveness for Web applications. It is worth to mention that besides Function Points and COSMIC, other size measures (e.g., dimensional measures like number of Web pages, media elements, client and server side scripts, etc.) have been proposed in the literature to be employed specifically for Web application development effort in combination with several estimation techniques [32] [33] [34] [35] [36] [37]. However, since our focus is on the use of FPA and COSMIC measurement methods, in the following we first report on investigations exploiting FPA (Section 2.4.1) and then those employing COSMIC (Section 2.4.2), also considering their extensions/adaptions.

We will discuss the main studies proposing conversion models from FPs into COSMIC in Section 4.1. It is worth noting that the analysis about the effectiveness of internal vs external conversion equations is related to the studies investigating the use of cross- vs within-company data sets for effort estimation. This topic has been widely analyzed in the last years producing different results (see e.g., [38]).

2.4.1. Using FPA and its extensions for Web effort estimation

FPA was employed by Ruhe *et al.* [39] to size 12 Web applications, such as B2B, intranet or financial, developed between 1998 and 2002. The aim was to compare the effort estimations obtained in terms of FPA with those achieved exploiting a size measure introduced specifically for Web applications, namely Web Objects [40]. Web Objects method represents an extension of FPA provided by Reifer who added four new Web-related components to the five function types of FPA, namely Multimedia Files, Web Building Blocks, Scripts, and Links. The results reported by Ruhe *et al.* [39] showed that the Web Objects-based linear regression model provided more accurate estimates than those achieved using Function Points. Successively, Web Objects measure was also used as size metric in the context of Web-COBRA [41], obtaining better results than those achieved with linear regression. Observe that Web-COBRA is a composite estimation method obtained by adapting COBRA [42] to be applied in the context of Web applications. The use of Web Objects for effort estimation was also exploited in other studies [11] [43]. In the first study [11], Web Objects were compared against COSMIC, by considering linear regression as estimation method, and the analysis of a data set of 15 Web applications revealed that the estimates achieved with a COSMIC based model were better. The second study [43] can be considered an extension of the previous one [11], by employing further applications in the data set, a further estimation technique (i.e., CBR), and exploring a different validation method. In that study, Web Objects were also compared against FPs. The results confirmed that Web Objects provided better results than FPs.

Other works proposed adaptations/extensions of FPA to size Web applications and estimate the development effort. In particular, the OOmFPWeb method [7] maps the FPs concepts into the primitives used in the conceptual modeling phase of OOWS, which is a method for producing software for the Web [44]. More recently, Abrahão *et al.* have also proposed a model-driven functional size measurement procedure, named OO-HFP, for Web applications developed using the OO-H method [45]. The approach has been validated by comparing its estimation accuracy with the one achieved by using the set of measures defined by Mendes *et al.* for the Tukutuku database

[32]. The results of the empirical study were promising since the obtained effort estimates were comparable with those obtained by using the Tukutuku measures, thus revealing that the OO-HFP approach can be suitable to estimate the development effort of model-driven Web applications. Recently, the accuracy of the estimates achieved with OO-HFP has been compared with the accuracy of estimates obtained by employing a set of design measures defined on OO-H conceptual models [46]. By employing 30 OO-H Web applications the analysis revealed that the linear regression model based on two OO-H design measures provided significantly better estimates than the linear model based on the OO-HFP measure, thus confirming that FPA can fail to capture some specific features of Web applications [47] [6].

Another FPA based approach able to automatically obtain a size estimation of Web applications from conceptual models produced with a model-driven development method has been provided by Fraternali *et al.* [8]. In particular, the software models were obtained by using WebML, a UML profile proposed to model Web applications [48]. An initial validation of the approach was performed by comparing the FPs counting computed automatically with the result achieved by two skilled analysts who manually sized the applications. The analysis revealed that the average error between the manual and the automated counting is in the range of the average error reported for the FPs counting of the two analysts [8].

2.4.2. Using COSMIC and its extensions for Web effort estimation

The first investigations of COSMIC were presented in two studies that exploited sets of Web applications developed by students [12] [9], obtaining different and contrasting results. Mendes *et al.* applied the COSMIC to 37 Web hypermedia systems developed by postgraduate and MSc students of the University of Auckland (NZ) [12]. However, the derived linear regression model did not present reasonable prediction accuracy, and replications of the empirical study were highly recommended. The second study [9] employed information on 44 Web applications (mainly Web portals, e-commerce sites, etc...) developed by academic students of University of Salerno (IT) and the built linear regression models provided encouraging results. However, the scientific literature has often debated on the industrial relevance of results coming from empirical studies with students [49] [50].

Anyhow, two other studies exploiting industrial data sets were conducted in the past to verify the effectiveness of the COSMIC measure as indicator of development effort when used in combination with linear regression [11] [13], obtaining encouraging results that motivated the investigation we present in this paper. In the first study [11], a preliminary investigation of COSMIC based on 19 Web applications developed by an Italian software company was performed and good results were obtained. On the other hand, the main research question addressed by Di Martino and Gravino [13] was to analyze differences in the results between an academic and an industrial data sets, using previously used data sets [9] [11].

Adaptations of COSMIC have been also provided to apply the method in specific contexts. In particular, a COSMIC-based size measurement procedure, named OO-HCFP, for sizing model-driven Web applications developed using the OO-H method has been presented by Abrahão *et al.* [51]. Several mapping and measurement rules have been devised for automatically deriving the size measure from the OO-H conceptual models. Moreover, Buglione *et al.* [16] investigated whether considering the COSMIC data movements E, X, R, and W rather than the total functional size improves effort estimation accuracy of models built with linear regression. The results showed that the estimates obtained by considering the total functional size were better (even if not statistically significant) than those achieved in terms of single data movements. With the aim to provide early effort estimations for Web applications in terms of COSMIC, De Marco *et al.* [52] investigated to what extend some COSMIC-based approximate can be employed. In particular, the number of COSMIC Functional Processes and the Average Functional Process approach proposed by the COSMIC method documentation were considered to obtain size approximations [53]. The results revealed that the first counting provides estimations better than the Average Functional Process approach but worse than the standard COSMIC method. De Marco et al. [52] exploited the same data employed in the current investigation (note that some summary measures were incorrectly reported in [52], this explains the difference with those reported in this paper (i.e., Table 1), please refer to the data reported in the current paper). As a consequence the effort estimation model based on COSMIC measure is the same. In any case, the goal of that investigation was completely different. Indeed, they investigated to what extend some COSMIC-based approximations (e.g., the Average Functional Process approach proposed by the COSMIC method documentation) can be employed.

The analysis reported in the present paper differs in several aspects from those of the above papers. First of all, the focus is on the comparison of two functional size measurement approaches, i.e., FPA and COSMIC that are representative of 1^{st} and 2^{nd} generation methods, and on the assessment of a two step approach for migrating from FPs to COSMIC. Moreover the design of the empirical study is different. Indeed, in the present paper we employed a further estimation technique, i.e., CBR, and further evaluation criteria and statistical analyses, i.e., boxplot of residuals and z and effect size.

3. The First Empirical Study: Comparing COSMIC and FPA for effort estimation

This section presents the empirical study we carried out to assess and compare COSMIC and IFPUG[2] measures for Web effort estimation.

In the following we first present the design of the study (Section 3.1), then we report the achieved results (Section 3.2). The discussion of the results (Section 3.3) concludes the section.

3.1. Design of the study

3.1.1. Data set

The data for our empirical study was provided by an Italian medium-sized software company, whose core business is the development of enterprise information systems, mainly for local and central government. Among its clients, there are health organizations, research centers, industries, and other public institutions. The company is specialized in the design, development, and management of solutions for Web portals, enterprise intranet/extranet applications (such as Content Management Systems, e-commerce, work-flow managers, etc.), and Geographical Information Systems. It has about fifty employees, it is certified ISO 9001:2000, and it is also a certified partner of Microsoft, Oracle, and ESRI.

This company provided us information on 25 Web applications they developed. In particular, this set includes e-government, e-banking, Web portals, and Intranet applications. All the projects were developed with SUN J2EE or Microsoft .NET technologies. Oracle has been the most commonly adopted DBMS, but also SQL Server, Access and MySQL were employed in some of these projects.

[2]We employed the FPA formulated by IFPUG and in the rest of the paper we will refer to this method as FPA or IFPUG

As for the collection of the information, the software company used timesheets to keep track of the Web application development effort. In particular, each team member annotated the information about his/her development effort on each project every day, and weekly each project manager stored the sum of the efforts for the team. Furthermore, to collect all the significant information to calculate the values of the size measure in terms of COSMIC, we defined a template to be filled in by the project managers. All the project managers were trained on the use of the questionnaires. One of the authors analyzed the filled templates and the analysis and design documents, in order to cross-check the provided information. The same author calculated the values of the size measure. As for the calculation of the size in terms of IFPUG, the company has always applied this FSM method to measure its past applications. Further details on how these data have been collected are discussed in Section 5.

Table 1 shows some summary statistics related to the 25 Web applications employed in our study[3]. The variables are EFF, i.e., the actual effort expressed in terms of person-hours, CFP, expressed in terms of number of COSMIC Function Points, and FP, expressed in terms of number of Function Points. Furthermore, we have reported the variables denoting the BFCs for COSMIC (Entry, Exit, Read, and Write), expressed in terms of number of COSMIC Function Points, and Function Points (i.e., EI, EO, EQ, ILF, and EIF), expressed in terms of number of unadjusted Function Points.

Figure 3 shows the boxplots of the distributions of these variables. We can observe that the boxplot of FP has one outlier and the box length and tails are more skewed than those of the boxplot of CFP. The figure also highlights that EFF has a different distribution with respect to CFP and FP. As for the single BFCs of COSMIC, we can note that the boxplots for Read and Exit are more skewed than the boxplots of Entry and Write. They have no outliers. Regarding the single BFCs of Function Points, the boxplots for EQ, ILF, and EIF have outliers and are more skewed than the boxplots of EI and EO.

[3] Raw data cannot be revealed because of a Non Disclosure Agreement with the software company.

Table 1: Descriptive statistics of EFF, CFP, FP, Entry, Exit, Read, Write, EI, EO, EQ, ILF, and EIF

Var	**Obs**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**
EFF	25	782	4537	2577	2686	988.14
CFP	25	163	1090	602.04	611	268.47
FP	25	89	915	366.76	304	208.65
Entry	25	31	227	121.7	122	57.07
Exit	25	27	316	122.3	110	71.99
Read	25	90	607	328.8	351	136.04
Write	25	0	120	29.2	20	31.86
EI	25	3	240	86.4	78	66.85
EO	25	24	203	100	94	57.37
EQ	25	21	323	129.2	105	84.83
ILF	25	0	271	40.88	31	61.61
EIF	25	5	142	43.33	32	37.68

3.1.2. Selected estimation methods

In our empirical analysis we employed as estimation techniques SLR, that is a model-based approach, and CBR, that is a Machine Learning-based solution, since they have been widely and successfully employed in the industrial context and in several researches to estimate development effort (see e.g., [12] [17] [37] [49] [54] [55] [56]).

SLR allows us to build estimation models to explain the relationship between the independent variable, denoting the employed size measure, and the dependent variable, representing the development effort. Thus, SLR allows us to obtain models of this type:

$$EFF = a + b * Size \tag{1}$$

where EFF is the dependent variable, $Size$ is the independent variable (i.e., CFP or FP), b is the coefficient that represents the amount the variable EFF changes when the variable $Size$ changes 1 unit, and a is the intercept. Once such a model is obtained, given a new software project for which an effort estimation is required, the project manager has to size it using the same unit of measure of the model, and to use this value in the regression equation to get the effort prediction.

CBR is an alternative solution to SLR. It is a Machine Learning technique that can be used for classification and regression. In the domain of effort estimation, it allows us to predict the effort of a new project (target case) by considering some similar applications previously developed, representing

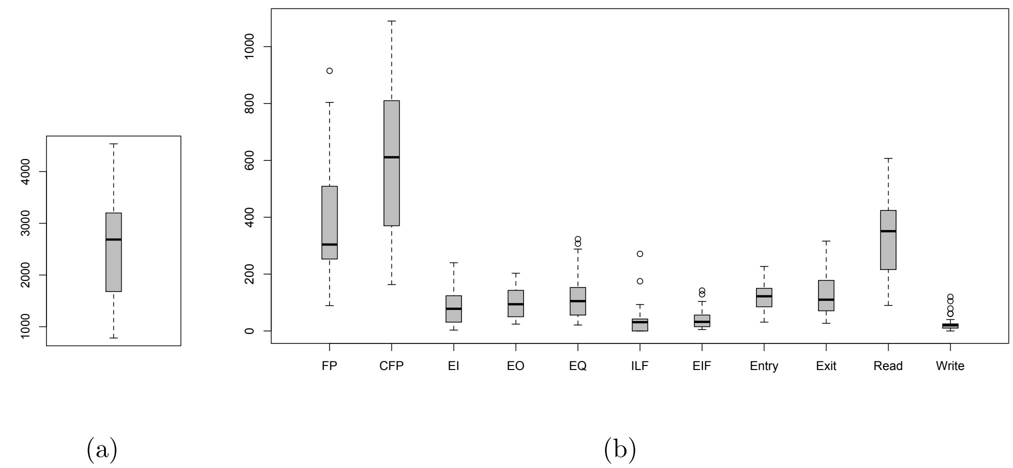


Figure 3: The boxplot of EFF (a) and FP, EI, EO, EQ, ILF, EIF, CFP, Entry, Exit, Read, and Write (b)

the case base (see e.g., [56]). In particular, similarly to SLR, once the new application is measured in terms of CFP or FP, the "similarity" between the target case and the other cases is measured, and the most similar past project (or more than one) is used, possibly with adaptations, to obtain the new effort estimation. To apply CBR, the project manager has to select an appropriate similarity function, the number of similar projects (analogies) to consider for the estimation, and the analogy adaptation strategy for generating the estimation.

In Sections 3.2.1 and 3.2.2 we provide the information on how we applied SLR and CBR in our study.

3.1.3. Validation method and evaluation criteria

In our analysis, we carried out an assessment to verify whether or not the obtained effort predictions are useful estimations of the actual development effort. To this end, we applied a cross-validation, splitting a data set into training and validation sets. Training sets are used to build the estimation models with SLR or to represent the case base when applying CBR, and validation sets are used to validate the obtained effort predictions. In particular, we exploited a leave-one-out cross-validation, which means that the original data set is divided into *n=25* different subsets (25 is the size of the original data set) of training and validation sets, where each validation set has just one observation. This validation method is widely used in empirical studies when dealing with small data sets. Furthermore, a recent study has shown advantages of leave-one-out cross-validation with respect to K-fold cross-validation to assess software effort models [57].

Regarding the evaluation criteria, we exploited Absolute Residuals (AR), i.e., $|Actual$ - $Predicted|$, where *Actual* is the actual effort and *Predicted* is the estimated effort, and to have a summary measure to accomplish the comparison among different estimation approaches we employed Median of AR (MdAR) since it is less sensitive to extreme values with respect the Mean of AR [58]. We also reported other summary measures, namely MMRE, MdMRE, Pred(25), that have been widely employed for effort estimation. However, they are reported only to allow for a comparison with previous researches published in this context and they are not used for the assessment of the achieved effort estimations. Indeed, the use of MMRE, and related measures, has been strongly discouraged in recent simulation studies, showing that MMRE wrongly prefers a model that consistently underestimates [59].

We also complemented the use of MdAR with the analysis of the boxplots of z, where $z = \frac{Predicted}{Actual}$, and boxplots of the residuals as suggested by Kitchenham *et al.* in [60]. Boxplots are widely employed in exploratory data analysis since they provide a quick visual representation to summarize the data using five values: median, upper and lower quartiles, minimum and maximum values, and outliers.

Moreover, we tested the statistical significance of the obtained results by using absolute residuals, to establish if COSMIC provided significantly better effort estimations than those achieved using FPA [60]. In particular, we performed the T-test (and the Wilcoxon signed rank test when absolute residuals were not normally distributed)[61] to verify the following null hypothesis "the two considered populations of absolute residuals have identical distributions".

In order to have also an indication of the practical/managerial significance of the results, we verified the effect size. Effect size is a simple way of quantifying the standardized difference between two groups. It is a good complement to the tests of statistical significance, since "whereas p-values reveal whether a finding is statistically significant, effect size indicates practical significance" [62]. In particular, we employed the Cliffs d non-parametric effect size measure because it is suitable to compute the magnitude of the difference when a non parametric test is used [62]. In the empirical software engineering field, the magnitude of the effect sizes measured using the Cliffs d can be classified as follows: negligible (d <0.147), small (0.147 to 0.33), medium (0.33 to 0.474), and large (d >0.474) [62].

3.2. Results of the empirical study

We first report on the application of COSMIC and FPA in combination with SLR (Section 3.2.1) to estimate Web application development effort and then the results obtained using CBR as estimation technique (Section 3.2.2).

3.2.1. Empirical results with SLR

We performed the SLR analysis to build the effort estimation models by using the data set of 25 Web applications of Table 1. To this end, we first verified the linear regression assumptions, i.e., the existence of a linear relationship between the independent variable and the dependent variable (linearity), the constant variance of the error terms for all the values of the independent variable (homoscedasticity), the normal distribution of the error terms (normality), and the statistical independence of the errors, in particular, no correlation between consecutive errors (independence).

In the following, we report on the analysis carried out to verify these assumptions. Note that the results of all the performed tests are intended as statistically significant at α=0.05 (i.e., 95% confidence level).

- Linearity. Figure 4(a) illustrates the scatter plot obtained by considering EFF and CFP. We can observe that the scatter plot shows a positive linear relationship between the involved variables. The linear relationship was also confirmed by the Pearson's correlation test (statistic=0.932 with p-value <0.01) [63] and the Spearman' rho test (statistic=0.942 with p-value <0.01) [61]. As for FP, from the scatter plot in Figure 4(b) we can observe a positive linear relationship with the variable EFF. The linear relationship was also confirmed by the Pearson's correlation test (statistic=0.782 with p-value <0.01) [63] and the Spearman' rho test (statistic=0.8 with p-value <0.01) [61]. These results also allow us to verify that CFP is more monotonously correlated with EFF than FP.

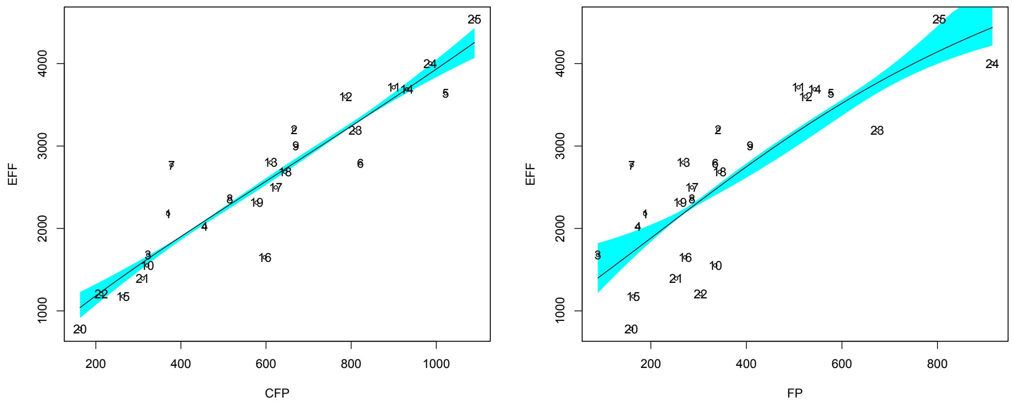
- Homoscedasticity. From the scatter plot shown in Figure 5 we can observe that the residuals fall within a horizontal band centered on 0, for both CFP and FP. However, some outliers may be noted, e.g., observations 7 and 16 for CFP and observations 7, 20, and 22 for FP. Thus, we further investigated the homoscedasticity assumption by performing a Breush-Pagan Test [64], with the homoscedasticity of the error terms as null hypothesis. This assumption is verified for the CFP, since the p-value (0.741) of the statistic (0.110) is greater than 0.05 and therefore the null hypothesis cannot be rejected. As for the FP, the null hypothesis cannot be rejected since p-value (0.44) of the statistic (0.596) was greater than 0.05.

- Normality. The analysis of Normal Q-Q plot for CFP in Figure 6(a) revealed that only some observations were not very close to the straight line and they should get closer attention ("outliers"). As for FP, the Normal Q-Q plot in Figure 6(b) was characterized by an S-shaped pattern revealing that there are either too many or two few large errors in both directions, i.e., the residuals have an excessive kurtosis [65]. Thus, in order to verify the normality assumption, we also used the Shapiro-Wilk Test [66], by considering as null hypothesis the normality of error terms. The results of the test for CFP revealed that the assumption can be considered to be verified since the p-value (0.389) of the statistic (0.959) was greater than 0.05 and thus the null hypothesis cannot be rejected. Differently, for FP the null hypothesis can be rejected since the p-value (0.022) of the statistic (0.904) was less than 0.05.

- Independence. The uncorrelation of residuals for consecutive errors has been verified by a Durbin-Watson statistic. For CFP the test provided a value quite close to 2 (1.543) and p-value (0.109) greater than 0.05, thus, we can assume that the residuals are uncorrelated. Differently, in the case of FP the test highlighted minor cases of positive serial correlation since a value not very close to 2 (1.207) was obtained with a p-value (0.0128) less than 0.05.

Taking into account the results of the performed analysis to verify linear regression assumptions (in particular, for the Normality and Independence) we decided to apply a log transformation to the variables in order to avoid an unfair comparison between CFP and FP in predicting development effort. The variables log transformed are denoted as Log(CFP) and Log(FP).

We also verified the presence of influential data points (i.e., extreme values which might unduly influence the models obtained from the regression analysis). As suggested in [67], we further analyzed the residuals plot and



(a) (b)

Figure 4: The scatter plot for EFF and CFP (a) and EFF and FP (b), resulting from the SLR

used Cook's distance to identify possible influential observations. In particular, the observations in the training set with a Cook's distance higher than $4/n$ (where n represents the total number of observations in the training set) were removed to test the model stability, by observing the effect of their removal on the model. If the model coefficients remained stable and the adjusted R^2 improved, the highly influential projects were retained in the data analysis. Figure 5(a) suggests that two observations seemed to have a large residual (i.e., observations 7 and 16). For observation 7, the Cook's distance was greater than 4/25, indicating that it was an influential observation, while for 16 the distance was less than 4/25. To check the model's stability, a new model was generated without observation 7. In the new model the independent variable remained significant, the adjusted R^2 improved a little, and the coefficient present similar value to the one in the previous model. Thus, the observation was not removed [67].

We also verified the presence of influential data points for the variable FP having residuals far from the horizontal band centered on 0 (see Figure 5(b)). This analysis revealed that observation 24 was characterized by a Cook's distance greater than 4/25. A new model was generated without observation 24 in the data set, which presented a coefficient similar to the one in the previous model and had a better adjusted R^2. So, no observation

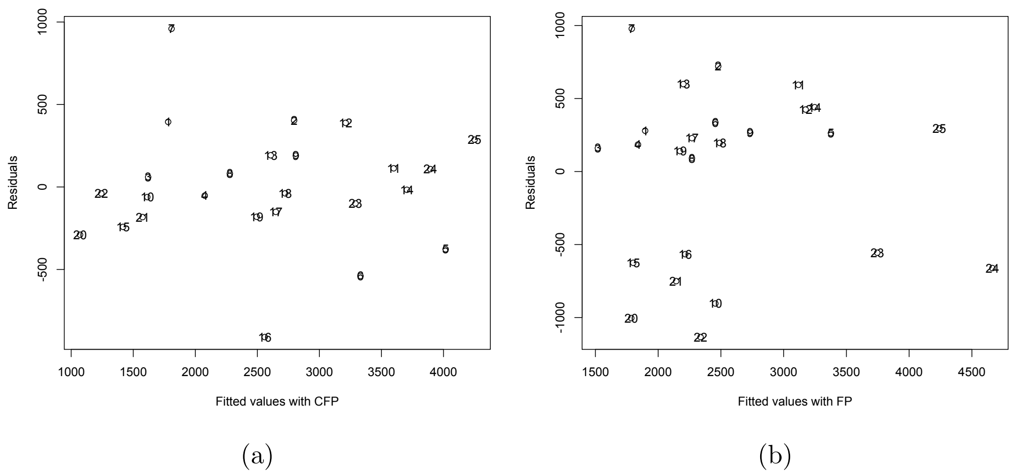


Figure 5: The scatter plot for residuals and predicted values for CFP (a) and FP (b), resulting from the application of SLR

was removed from the data set.

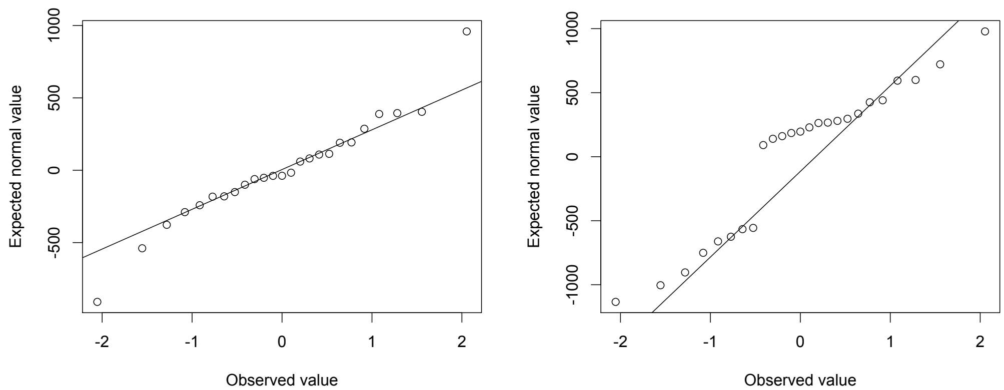
Table 2 shows some statistics about the model obtained with SLR by considering Log(CFP) as independent variable. A high R^2 value (and corresponding adjusted R^2 value) is an indicator of the goodness of the model, since it measures the percentage of variation in the dependent variable explained by the independent variable. Other useful indicators are the F-value and the corresponding p-value (denoted by Sign. F), whose high and low values, respectively, denote a high degree of confidence for the prediction. Moreover, we performed a t-statistic and determined the p- and the t-values of the coefficient and the intercept in order to evaluate their statistical significance. A p-value less than 0.05 indicates that we can reject the null hypothesis and the variable is a significant predictor with a confidence of 95%. As for the t-value, a variable is significant if the corresponding t-value is greater than 1.5.

The equation of the regression model obtained for Log(CFP) is:

$$Log(EFF) = 2.74 + 0.8 * Log(CFP) \tag{2}$$

and when it is transformed back to the original raw data scale we obtain:

$$EFF = 15.53 * CFP^{0.8} \tag{3}$$



(a) (b)

Figure 6: The Q-Q plot for residuals for CFP (a) and FP (b), resulting from the application of SLR

Table 2: The results of the SLR analysis with COSMIC on Log(CFP)

Variable	**Value**	**Std. Err**	**t-value**	**p-value**
Coefficient	0.8	0.06	12.64	< 0.01
Intercept	2.74	0.4	6.87	< 0.01

$\mathbf{R}^2$	**Adjusted** R^2	**Std. Err**	**F**	**Sign. F**
0.87	0.87	0.16	159.8	< 0.01

We can observe that the model described by Equation 2 is characterized by a high R^2 value (0.87), a high F value (159.8), and a low p-value (<0.01), indicating that a prediction is possible with a high degree of confidence (see Table 2). The t-values and p-values for the corresponding coefficient and the intercept present values greater than 1.5 and less than 0.05, respectively. Thus, the predictors can be considered important and significant.

Table 3 shows the results of the application of the SLR by considering Log(FP) as independent variable. We can observe that the coefficient and the intercept can be considered accurate and significant as from the t-statistic, but the R^2 and F values are lower than those obtained with Log(CFP).

To evaluate the prediction accuracy of the models obtained with SLR, we performed the leave-one-out cross-validation, whose results are reported

Table 3: The results of the SLR analysis with Function Points on Log(FP)

Variable	**Value**	**Std.Err**	**t-value**	**p-value**
Coefficient	0.56	0.12	4.53	<0.01
Intercept	4.47	0.73	6.12	<0.01

$\mathbf{R}^2$	**Adjusted** R^2	**Std. Err**	**F**	**Sign. F**
0.47	0.45	20.55	0.33	<0.01

Table 4: The results of the validation for SLR

Variable	**MdAR**	**MMRE**	**MdMRE**	**Pred(25)**
CFP	180	0.12	0.07	0.92
FP	515	0.29	0.18	0.68

in Table 4[4]. We can observe that the MdAR value achieved with the CFP based model is more than two times lower than the one obtained with the FP based model, thus highlighting much better results with COSMIC.

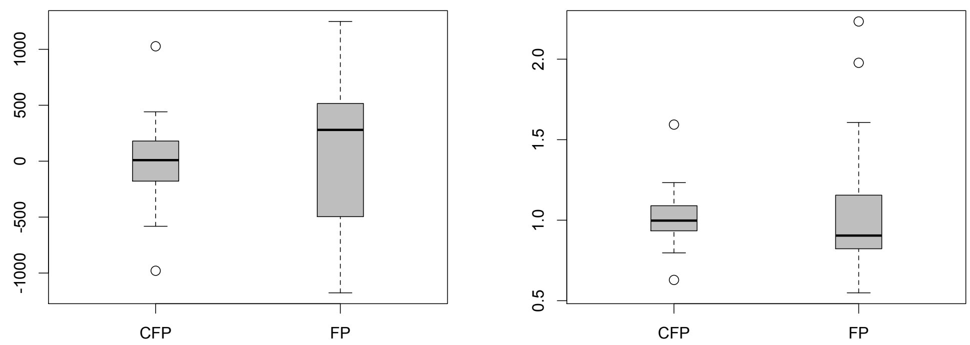
These results are confirmed by the boxplots of residuals and of z shown in Figure 7. Indeed, even if the boxplot of residuals for CFP has two outliers, its median is closer to zero. Moreover its box length and tails are less skewed than those of the boxplot of residuals for FP (see Figure 7(a)). As for boxplots of z, CFP has a median closer to 1 and again the box length and tails are less skewed than those of FP (see Figure 7(b)).

This finding is corroborated by the tests on the statistical significance of the results by using absolute residuals [49] [60]. In particular, the Wilcoxon test revealed that the estimations obtained with CFP are significantly better than those obtained with FP (p-value < 0.01) with a large effect size (d=0.63). Observe that we applied the Wilcoxon test since the absolute residuals obtained with CFP were not normally distributed, as highlighted by the Shapiro test (p-value < 0.01).

3.2.2. Empirical results with CBR

Before applying CBR, we verified which one of the two variables FP and CFP is more informative for EFF, by considering the correlation between distance matrices. A high correlation between distances of EFF values and distances of CFP values can indicate that projects similar according to COS-

[4]Notice that the original raw data scale models are used to obtain the effort predictions



(a) (b)

Figure 7: The boxplots of residuals (a) and z (b) obtained with SLR

MIC size are similar according to effort. To this end, we applied the Mantel test [68], which checks the correlation between two distance matrices. It is a non-parametric test that computes the significance of the correlation through permutations of the rows and columns of one of the input distance matrices. The test statistic is the Pearson product-moment correlation coefficient r. The values for r can fall in the range of -1 to +1, where being close to -1 indicates strong negative correlation and +1 indicates strong positive correlation. An r value of 0 indicates no correlation. In particular, we performed the Mantel test by considering the null hypothesis that the two matrices, i.e., the EFF distances and the CFP distances, are unrelated. Similarly, we performed the test considering as matrices the EFF distances and the FP distances. For both CFP and FP, the results of the test revealed that we can reject the null hypothesis that the correlation matrices are unrelated since we obtained p-values less than 0.05. In the case of EFF and CFP distances, we obtained $r = 0.824$, while in the case of EFF and FP distances, the test was characterized by r=0.579. Thus, the correlation matrix entries are positively associated and CFP is more informative for EFF than FP.

In order to apply CBR we exploited the tool ANGEL [56] that implements the Euclidean distance as similarity function using variables normalized between 0 and 1 and allows users to choose the relevant features/predictors, the number of analogies, and the analogy adaptation technique for generating the estimations. As for the predictors, we used the variables CFP and FP. The selection of the number of analogies is a key task, since it refers to the number of similar cases to use for estimating the effort required by the target case. Since we dealt with a not so large data set, we used 1, 2, and 3 analogies, as suggested in many similar works (see e.g., [49]). To obtain the estimation once the most similar cases were determined, we employed three widely adopted adaptation strategies: the mean of k analogies, i.e., simple average, the inverse distance weighted mean (see e.g., [49] [69]), and the inverse rank weighted mean (see e.g., [56]). So, performing a leave-one-out cross-validation, we obtained 25 estimations and the corresponding residuals, for each selection of the number of analogies and of the analogy adaptation techniques. Indeed, each estimate was achieved by selecting an observation from the whole data set of 25 Web applications (in Table 1) as validation set and employing the remaining observations (i.e., 24) as training set. This was performed 25 times.

Table 5 shows the results obtained with CBR. We can observe that the MdAR values achieved with CFP are much better than those achieved with FP for all the considered configurations. Furthermore, the best result achieved with CFP (i.e., with k=3 as number of analogies and mean of k analogies as adaptation strategy) is two times lower than the best result obtained with FP (i.e., with k=3 as number of analogies and inverse rank weighted mean as adaptation strategy). Similarly to the SLR results, the boxplots of residuals and z for CFP have box length and tails less skewed than those of the boxplots of residuals for FP (see Figure 8(a) and (b)).

These results are corroborated by the tests on the statistical significance of the results by using absolute residuals [49] [60]. In particular, we compared the absolute residuals achieved with CFP using k=3 as number of analogies and mean of k analogies as adaptation strategy and the absolute residuals obtained with FP using k=3 as number of analogies and inverse rank weighted mean as adaptation strategy. The results of the Wilcoxon test revealed that the estimations obtained with CFP are significantly better than those obtained with FP (p-value=0.03) with a small effect size (d=0.19).

Thus, the results with CBR confirm that CFP leads to better effort predictions than FP.

We can also observe that CBR provided slightly worse results than SLR, in terms of MdAR (see Tables 4 and 5). This result is confirmed by the analysis of the boxplots of residuals and z. The statistical analysis performed on absolute residuals revealed that the difference in the absolute residuals ob-

Table 5: The results of the validation for CBR

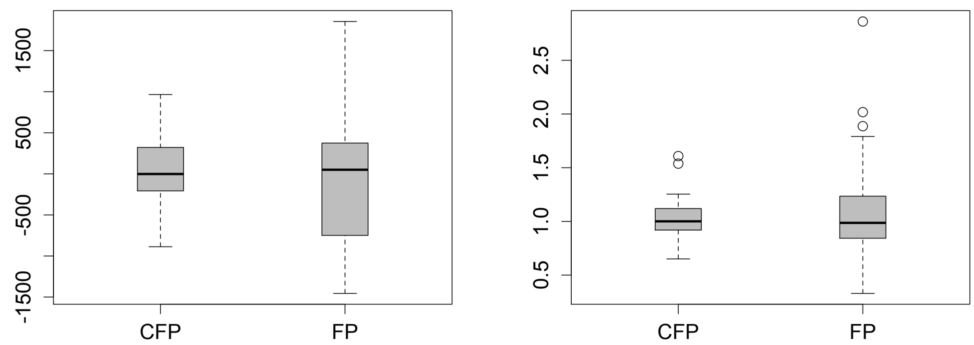
CBR with	MdAR	MMRE	MdMRE	Pred(25)
Using CFP as predictor				
k=1; mean of k analogies	362	0.17	0.12	0.80
k=2; mean of k analogies	245	0.16	0.12	0.80
k=3; mean of k analogies	218	0.15	0.10	0.84
k=1; inverse distance weighted mean	362	0.18	0.12	0.80
k=2; inverse distance weighted mean	262	0.16	0.11	0.88
k=3; inverse distance weighted mean	282	0.15	0.12	0.88
k=1; inverse rank weighted mean	362	0.18	0.12	0.80
k=2; inverse rank weighted mean	291	0.16	0.12	0.88
k=3; inverse rank weighted mean	286	0.15	0.12	0.88
Using FP as predictor				
k=1; mean of k analogies	535	0.44	0.19	0.56
k=2; mean of k analogies	576	0.32	0.21	0.52
k=3; mean of k analogies	449	0.32	0.20	0.60
k=1; inverse distance weighted mean	535	0.44	0.19	0.56
k=2; inverse distance weighted mean	470	0.35	0.20	0.60
k=3; inverse distance weighted mean	468	0.35	0.20	0.64
k=1; inverse rank weighted mean	535	0.44	0.19	0.56
k=2; inverse rank weighted mean	435	0.35	0.18	0.68
k=3; inverse rank weighted mean	485	0.34	0.18	0.68

tained with the two techniques is not statistically significant (p-value=0.05), with a small effect size ($d = 0.23$), when using CFP as independent variable. However, note that the p-value is equal to the threshold 0.05. In the case of using FP, the p-value obtained with the Wilcoxon test is 0.56, so the difference in the absolute residuals achieved with the two techniques is not statistically significant. The effect size in this case is negligible (d=0.06).

3.3. Answering $RQ1_a$

The results reported in Tables 4 and 5 suggest that, on our data set, CFP can be considered a good indicator of the development effort, when used in combination with the two analyzed estimation methods (i.e., SLR and CBR). Moreover, the effort estimates achieved with CFP are significantly better than those obtained with FP, with an improvement of 65%[5] in terms of MdAR value and a large effect size in the case of SLR. Thus, the software company involved in our study should profitably move from FPA to COSMIC to improve the quality of its effort estimations.

[5]The average percentage improvement has been calculated as (MdAR of the FP based model - MdAR of the CFP based model)/MdAR of the FP based model).



(a) (b)

Figure 8: The boxplots of residuals (a) and z (b) obtained with CBR

Summarizing, we can positively answer the first research question: *COSMIC measure is significantly better than FPs for estimating Web application development effort by simple linear regression and case based reasoning.*

3.4. Answering $RQ1_b$

To answer the second research question, we first verified the correlation between each BFC and the effort. To this aim, we applied the Spearman rho test, whose results are reported in Table 6.

We can observe that, as for COSMIC, all the four BFCs are statistically significant correlated with EFF since the p-values are less than 0.01. In particular, we can observe that three of them (i.e., Entry, Exit, and Read) have a rho statistic greater than 0.8 that can be considered a good value [61], while Write was characterized by a lower value. Among them, the Read BFC resulted to be the more informative one for EFF, having the highest rho statistic (0.919). This result is confirmed by the analysis of the distribution of the BFCs with respect to the final size, whose results are reported in Table 6. These results are in line with the type of Web applications we dealt with. Indeed, the applications in our data set mainly provide information to the users, by requiring many queries to the persistent layers of the applications, being counted in COSMIC as Reads.

Table 6: Correlation among EFF and each BFC of the COSMIC and FPA method

BFC	**rho statistic**	**p-value**
Entry	0.823	<0.01
Exit	0.859	<0.01
Read	0.919	<0.01
Write	0.535	<0.01
EI	0.741	<0.01
EO	0.324	0.11
EQ	0.671	< 0.01
ILF	0.321	0.118
EIF	0.141	0.5

From these results we can conclude that: *all the COSMIC BFCs are significantly correlated with EFF and Read resulted to be the one more informative for predicting EFF.*

The same kind of analysis has been performed for FPs, revealing that only EI and EQ are statistically significant correlated with EFF (see the results of the Spearman rho test reported in Table 6). In particular, EI resulted to be the more informative for EFF (rho statistic = 0.741), but its statistic does not reach the level of 0.8. The analysis of the distribution of the Function Point BFCs with respect to the EFF suggests that the main contribution to the final size comes from EQ, EO, and EI. This leads to the same kind of observations done for COSMIC on the prevalent type of operations in the considered Web applications. Nevertheless, these lower values confirm that FPA is missing to fully capture the size of a Web application. Moreover, these results further suggest that COSMIC, and its single BFCs, are more informative for EFF than FPs and its single BFCs, for the considered kind of Web applications

From these results we can conclude that: *only EI and EQ are significantly correlated with EFF among the FP BFCs and EI resulted to be the more informative for predicting EFF.*

4. The Second Empirical Study: Assessing the use of 2SEP

From the results of our first empirical study, it is clear that the software company in our study can benefit from migrating to COSMIC, since on the considered projects this method provided significantly better development

Table 7: Distribution of the BFCs with respect to the final size in terms of CFP

FSM method	**Entry**	**Exit**	**Read**	**Write**
COSMIC	20%	19%	56%	5%

FSM method	**EI**	**EO**	**EQ**	**ILF**	**EIF**
FPA	22%	25%	32%	10%	11%

effort estimates. Our second empirical study aims at understanding how easily this migration can be achieved. As mentioned in the introduction of this paper, a company interested in the adoption of COSMIC has to build an estimation model with this measure. This basically requires historical data based on COSMIC that can be obtained by manually remeasuring all the applications previously developed. This task not only requires a lot of time, but in some cases might not even be possible (e.g., due to the lack of appropriate documentation). The reuse of data based on FPA could be very valuable to address the problem, provided that there is a way to obtain the size in terms of CFPs from the size in terms of FPs. As it was pointed out by Abran *et al.* [53], FPA and COSMIC measures focus on different aspects of software systems since they are based on different basic functional components. Thus, "exact mathematically-based conversion formulae from sizes measured with a 1^{st} generation method to COSMIC sizes are impossible". A possible way to address the problem, also suggested in the COSMIC documentation [53], is to search for some "statistically-based conversion formulae".

Some researchers have been investigating the suitability and the effectiveness of such an approach by trying to build conversion equations for different data sets. In particular, linear and non-linear equations have been built on the raw data and on the log-transformed data, respectively [14]. Also, more sophisticated techniques, such as piecewise regression, have been employed for building non-linear models [15].

The results reported in the literature [14] [15] [22] [23] [70] [71] [72] [73] [74] reveal that a statistical conversion is possible, thus supporting the suggestions provided in the COSMIC documentation [53]. The studies also showed that both linear and non-linear models should be analyzed to identify the best correlation. Furthermore, more complex techniques, such as piecewise regression [15]), did not provide significantly better results, being at the same time hardly applicable.

The aim of our second empirical study was to analyze whether it is possible to reuse the FP → CFP conversion equations proposed in the literature (i.e., external conversion equations) to apply the two-step process shown in Figure 1 (named 2SEP) for building effort estimation models. In other words, we assessed if, given the size of past projects in terms of FPs, it is possible to convert them by means of some equations into COSMIC measure to build an effort estimation model. Furthermore, we also considered the use of conversion equations built on a (small) data set of the company taken into account (i.e., internal conversion equations).

In the following, before presenting the design (Section 4.3) and the results (Section 4.4) of our second empirical study, we provide a brief description of the external conversion equations we decided to employ (Section 4.1) and we describe the construction of the internal conversion equations (Section 4.2).

4.1. External conversion equations from previous studies

In our study we took into account the results of two previous investigations that analyzed the relationship between the sizes expressed in terms of FPs and of CFPs, namely [14] and [75].

The aim of Cuadrado-Gallego *et al.* [14] was to carry out a review of previous investigations that mainly exploited linear regression analysis for converting FPs into CFPs, i.e., by constructing an equation as:

$$CFP_{FP} = a + b * FP \tag{4}$$

where the dependent variable CFP_{FP} represents the estimated COSMIC size and the independent variable FP represents the size in terms of FPs.

Moreover, Cuadrado-Gallego *et al.* were also the first to propose an analysis on a non-linear relation between CFP_{FP} and FP, by exploiting the log transformation of the variables in the application of linear regression analysis. Thus, the equation obtained is of this form:

$$Log(CFP_{FP}) = Log(a) + b * Log(FP) \tag{5}$$

which, when transformed back to the original raw data scale, gives the equation:

$$CFP_{FP} = a * FP^{b} \tag{6}$$

For the evaluation, they employed nine publicly available data sets: six of them were obtained from previous studies (i.e., named *fet99*[76], *fet99-2*[77], *ho99*[71], *vog03*[77], *abr05*[22], and *des06*[23]). Three additional data sets

Table 8: Parameters of the equations in [14]

	Linear								
Data set	fet99	fet99-2	ho99	vog03	abr05	des06	jjcg06	jjcg07	jjcg0607
b	1.12	1.14	1.03	1.2	0.84	1	0.82	0.86	0.69
a	-6.23	-7.6	-6.6	-86.8	18	-3.23	-36.6	0.19	13.04
R^2	0.98	0.97	0.98	0.99	0.91	0.93	0.7	0.86	0.85
	Non-Linear								
Data set	fet99	fet99-2	ho99	vog03	abr05	des06	jjcg06	jjcg07	jjcg0607
b	1.11	1.12	1.14	1.18	0.96	1.07	1.17	1.02	0.9
a	0.64	0.62	0.52	0.28	1.08	0.67	0.27	0.75	1.26
R^2	0.99	0.97	0.99	0.94	0.88	0.95	0.82	0.73	0.87

were included in the paper: the first two (named *jjcg06* and *jjcg07*) contained 21 and 14 observations, respectively, and were obtained in two different studies conducted with academic students, while the third one (named *jjcg0607*) was obtained by merging the first two.

The parameters of the linear and non-linear conversion equations obtained for the above data sets are reported in Table 8[6], respectively. In particular, the tables show, for each employed data set, the equation parameters a and b, and the R^2 value. We can observe that the linear conversion equations reported in Table 8 (top) are characterized by a coefficient quite close to 1, and the non-linear equations (see Table 8 (bottom)) have the coefficient values even closer to 1. These results seem to suggest that a conversion equation based on the assumption of 1 CFP $\cong$ 1 FP could be possible. Cuadrado-Gallego *et al.* argued that a 1 to 1 conversion factor cannot be attributed to anything other than an influential coincidence. Indeed, even if both FPA and COSMIC measure the functional size of the software, they are taking in consideration different characteristics and also different counting procedures. [14].

Lavazza [75] also exploited some of the data used in previous work [14][47] to empirically assess and compare linear and non-linear models against Piecewise Linear Regression, with a special emphasis on the role of outliers. He built 6 linear and 6 non-linear models, whose information can be found in

[6]Note that we applied the procedure employed in [14] for building the conversion equations exploiting the data sets that they published and in 5 cases (namely *jjcg0607* linear and non-linear, *ho99* non-linear, *vog03* non-linear) we found some differences in the obtained models with respect to [14]. In the table we report the values we obtained.

Table 9: Parameters of the equations in [75]

	Linear					
Data set	vog03	des06	vanH07	jjcg06	jjcg07	jjcg0607
b	0.78	0.97	1.05	0.7	0.86	0.65
a	-3.8	-5.9	-17.9	-2.4	0.2	19.07
R^2	0.94	0.97	0.95	0.65	0.86	0.85
	Non-Linear					
Data set	vog03	des06	vanH07	jjcg06	jjcg07	jjcg0607
b	1.2	1.03	1.09	1.62	1.12	0.97
a	0.28	0.84	0.61	0.27	0.46	0.87
R^2	0.98	0.97	0.95	0.82	0.83	0.93

Table 9. These equations differ from the one in the work of Cuadrado-Gallego *et al.* [14] since Lavazza eliminated from the data sets the outliers affecting the models. As already mentioned at the beginning of Section 4, we did not consider the Piecewise Regression since it did not provide significantly better results than SLR, being at the same time hardly applicable [15].

4.2. Internal conversion equations built on our data set

To build internal conversion equations with SLR we first verified the relationship between the dependent and independent variables CFP and FP, respectively, by assessing linear regression assumptions, i.e., linearity, homoscedasticity, normality, and independence. In particular, the Spearman' rho test revealed that there was a positive linear relationship between CFP and FP (statistic=0.848 with p-value $<$0.01), while the Breush-Pagan Test showed that homoscedasticity assumption was verified since the p-value (0.674) of the statistic (0.176) was greater than 0.05. On the other hand, the normality assumption for the residuals cannot be considered to be verified since the p-value (0.243) of the statistic (0.949) was greater than 0.05. As for the independence, the Durbin-Watson statistic was not close to 2 (1.34). As a consequence, we also applied a log-transformation of the data and we considered both linear and non-linear conversion equations as done in previous investigations (e.g., [14], [75]).

Since we were interested to verify the possibility for the company involved in our study to build its own convertibility equation using a small sample of projects from their own organization instead of using someone else equations, we employed a data set of 5 observations[7].

4.3. Design of the study

The empirical study performed to answer research questions $RQ2_a$ and $RQ2_b$ employs the same data set used in the first empirical study (see Section 3.1.1), whose descriptive statistics are shown in Table 1.

For the application of 2SEP we have to select an FP $\rightarrow$ CFP conversion equation and a model building technique to obtain the effort estimation model. We employed both external and internal conversion equations. Regarding the model building technique, we used SLR since in the first empirical study it performed better than CBR (see Section 3.3). We verified linear regression assumptions for each built model and as a result we performed a log transformation of the dependent and independent variables employed, as done for the first research question.

When exploiting external conversion equations, we used those reported in Tables 8 and 9. Moreover, given its immediate applicability, we also investigated 2SEP using a 1 to 1 conversion factor (named from here on 1-1 Conv). Thus, as first step of 2SEP, we exploited 15 linear, 15 non-linear and the *1-1 Conv* conversion equations, to obtain 31 new data sets, where the 25 Web applications are expressed in terms of estimated CFPs. Then, as second step of 2SEP, we applied SLR on each of them and obtained estimation models of this type: $EFF = a * (CFP_{FP})^b$, where EFF is the dependent variable and CFP_{FP} is the independent variable. As mentioned in previous section CFP_{FP} represents the estimated COSMIC size through the chosen FP $\rightarrow$ CFP conversion equation.

Concerning the assessment of 2SEP with external conversion equations, we used again a leave-one-out cross-validation for each of the employed conversion equations. In particular, we simulated the situation where the company has a historical data set of 24 projects (i.e., the training set) sized with FPA and the project manager is willing to estimate the effort for a new project (i.e., the validation set) sized with COSMIC. This setting reflects what could happen in reality in a software company willing to migrate from FPA to COSMIC. Thus, the effort predicted of a new project is obtained by giving as input to the estimation model $EFF = a * (CFP_{FP})^b$, built on the

[7]A rule of thumb in regression analysis is that 5 to 10 records are required for every variable in the model [17]

training set of 24 observations, the size of the new project (i.e., the observation in the validation set), manually counted in terms of COSMIC[8]. In our investigation, we carried out this approach 25 times, each time selecting one project as the new one and then evaluating the effort estimation accuracy.

To apply 2SEP with internal conversion equations, we first built the conversion equation by using 5 of the 25 applications of the data set provided by the company, then we applied this conversion equation on the remaining 20 applications, thus obtaining 20 estimated COSMIC sizes. As second step of 2SEP we applied SLR on the data set consisting of 5 applications measured with the standard COSMIC method and 20 applications whose COSMIC size was obtained with the internal conversion equation built in the first step. In order to validate the obtained effort estimation models we considered again the leave-one-out cross validation. To reduce selection biases, we repeated the above procedure 5 times by obtaining 5 internal conversion equations (i.e., one for each of the 5 data sets consisting of 5 randomly selected different web applications from the original data set). To compare the accuracy of the effort estimations obtained with 2SEP using internal conversion equations with respect to the accuracy of the effort estimations obtained with the FP based model, we considered the mean of the 5 residuals obtained for each observation (i.e., using the 5 effort estimation models built on the 5 data sets by using each of the 5 internal conversion equations).

As for the evaluation criteria, we used again summary measures, boxplots of residuals and of z, statistical tests and effect size as done in the first empirical study (see Section 3.1.3 for their description).

4.4. Results

We applied SLR to build effort estimation models for each of the 31 data sets obtained by exploiting the 15 linear, 15 non- linear, and the 1-1 Conv conversion equations described in Section 4.1. Then, to evaluate the prediction accuracy of these effort estimation models we performed a leave-one-out cross validation as designed in the previous section.

The prediction accuracy in terms of MdAR (and other summary measures reported just for comparison with previous studies) is shown in Table 10 for

[8]Clearly when using 1-1 Conv, the estimation model, built starting from the historical data set of 24 projects sized with FPA, simply becomes $EFF = a * FP^b$. It differs from the Function Points based model presented in Section 3.2 since the new project is not sized in terms of FPA but COSMIC is exploited.

each of the models built with 2SEP. To facilitate the comparison with the results achieved by employing FP as size measure, in Table 10 we also report the results achieved with the FP based estimation model.

We can observe that 2SEP leads to worse performances than the FP based model in terms of MdAR in almost all the cases exploiting external conversion equations. We also note that the estimates achieved with 1-1 Conv are by far worse than those achieved with the FP based model, with an error that is about 50%. Only four non-linear conversion equations provide better results than FPs, namely *fet99(NL)*, *fett99-2(NL)*, and *ho99(NL)* among those obtained from data sets provided in [14], and *jjcg0607(NL)* among the conversion equations obtained from [75]. These results are also confirmed by the boxplots of residuals and z reported in Figures 9, 10, 11 and 12. Indeed, the median of the boxplots of residuals for *fet99(NL)*, *fett99-2(NL)*, and *ho99(NL)* in Figure 9 and *jjcg0607(NL)* in Figure 11 is closer to zero than the median of the boxplot for FP and the box length and tails of the boxplots of residuals for *fet99(NL)*, *fett99-2(NL)*, *ho99(NL)*, and *jjcg0607(NL)* are less skewed than those of the boxplot for FP. Moreover, even if the box length and tails of the boxplot of residuals for FP are more skewed than those of boxplots obtained in the remaining cases, its median is closer to the zero (see Figures 9 and 11). As for the boxplots of z, those obtained with the FP and the *fet99(NL)*, *fett99-2(NL)*, *ho99(NL)*, and *jjcg0607*(NL) based models have the median closer to 1 than the others.

Concerning the results achieved with 2SEP employing internal conversion equations, we can note that both the linear and non-linear models are characterized by an MdAR value better than the one obtained with the FP based model. As expected, the internal conversion equations allowed us to achieve better results than the external conversion equations. These results are confirmed by the boxplots of residuals and z shown in Figure 13.

The results in terms of MdAR and boxplots of residuals and z are corroborated by the tests on the statistical significance of the results by using absolute residuals. In particular, the results of the Wilcoxon test reveal that the estimations obtained with 2SEP are significantly worse (p-value <0.05) than those obtained with the FP based model in 15 out of 31 cases considering external conversion equations, with a medium or large effect size. In the other 16 cases, i.e., *fet99*(L), *fet99-2*(L), *vog03*(L), *des06*(L), *fet99(NL)*, *fet99-2(NL)*, *ho99(NL)*, and *des06*(NL) for the models built taking into account the data sets provided in [14], *vanH07(L)*, *des06(NL)*, *vanH07(NL)*, *jjcg06(NL)*, *jjcg07(NL)* and *jjcg0607(NL)* for the models built using the con-

Table 10: Results about effort prediction achieved with 2SEP (for all the considered conversion equations) and the FP based estimation model. (L) and (NL) denote linear and non-linear models, respectively

Conversion equations from		**MdAR**	**MMRE**	**MdMRE**	**Pred(25)**
Cuadrado-Gallego *et al.* study [14]	fet99(L)	721	0.36	0.27	0.44
	fet99-2(L)	698	0.35	0.25	0.48
	ho99(L)	878	0.43	0.35	0.35
	vog03(L)	874	0.43	0.30	0.40
	abr05(L)	1144	0.57	0.52	0.04
	des06(L)	902	0.45	0.37	0.28
	jjcg06(L)	1444	0.71	0.65	0.04
	jjcg07(L)	1202	0.58	0.54	0.04
	jjcg0607(L)	1780	0.80	0.78	0.04
	fet99(NL)	440	0.28	0.16	0.60
	fet99-2(NL)	415	0.27	0.14	0.68
	ho99(NL)	449	0.30	0.16	0.60
	vog03(NL)	1121	0.55	0.44	0.16
	abr05(NL)	1231	0.61	0.56	0.04
	des06(NL)	826	0.41	0.31	0.36
	jjcg06(NL)	1348	0.64	0.56	0.04
	jjcg07(NL)	1226	0.59	0.54	0.04
	jjcg0607(NL)	2135	0.91	0.90	0.04
Lavazza study [75]	vog03 (L)	1234	0.59	0.51	0.12
	des06 (L)	821	0.41	0.34	0.40
	vanH07(L)	717	0.37	0.29	0.48
	jjcg06(L)	1444	0.69	0.60	0.08
	jjcg07(L)	1025	0.50	0.43	0.24
	jjcg0607(L)	1582	0.75	0.69	0.04
	vog03(NL)	897	0.34	0.37	0.20
	des06(NL)	693	0.27	0.29	0.36
	vanH07(NL)	768	0.29	0.32	0.36
	jjcg06(NL)	685	0.37	0.26	0.48
	jjcg07(NL)	753	0.29	0.32	0.36
	jjcg0607(NL)	452	0.19	0.17	0.80
1-1 Conv		750	0.39	0.31	0.44
Internal(L)		379	0.21	0.16	0.74
Internal(NL)		399	0.22	0.15	0.74
FP		515	0.29	0.18	0.68

Table 11: Comparison among estimations achieved with CFP_{FP} and FP based models. (L) and (NL) denote linear and non-linear conversion equations, respectively

Conversion equations from		**T-Wilcoxon test p-value**	**Effect size**
Cuadrado-Gallego *et al.* study [14]	fet99(L)	0.85	0.05 (negligible)
	fet99-2(L)	0.98	0.02 (negligible)
	ho99(L)	0.17	0.28 (small)
	vog03(L)	0.44	0.03 (negligible)
	abr05(L)	<0.01	0.71 (large)
	des06(L)	0.07	0.34 (medium)
	jjcg06(L)	<0.01	0.69 (large)
	jjcg07(L)	<0.01	0.68 (large)
	jjcg0607(L)	<0.01	0.92 (large)
	fet99(NL)	0.22	0.2 (small)
	fet99-2(NL)	0.13	0.24 (small)
	ho99(NL)	0.31	0.17 (small)
	vog03(NL)	<0.01	0.56 (large)
	abr05(NL)	<0.01	0.74 (large)
	des06(NL)	0.24	0.22 (small)
	jjcg06(NL)	<0.01	0.72 (large)
	jjcg07(NL)	<0.01	0.68 (large)
	jjcg0607(NL)	<0.01	0.95 (large)
Lavazza study [75]	vog03(L)	<0.01	0.83 (large)
	des06(L)	0.02	0.42 (medium)
	vanH07(L)	0.18	0.24 (small)
	jjcg06(L)	<0.01	0.92 (large)
	jjcg07(L)	<0.01	0.68 (large)
	jjcg0607(L)	<0.01	0.95 (large)
	vog03(NL)	0.01	0.40 (medium)
	des06(NL)	0.09	0.23 (small)
	vanH07(NL)	0.06	0.27 (small)
	jjcg06(NL)	0.34	0.13 (negligible)
	jjcg07(NL)	0.06	0.26 (small)
	jjcg0607(NL)	0.32	0.2 (small)
1-1 Conv		0.08	0.34 (medium)
Internal(L)		<0.01	0.63 (large)
Internal(NL)		<0.01	0.69 (large)

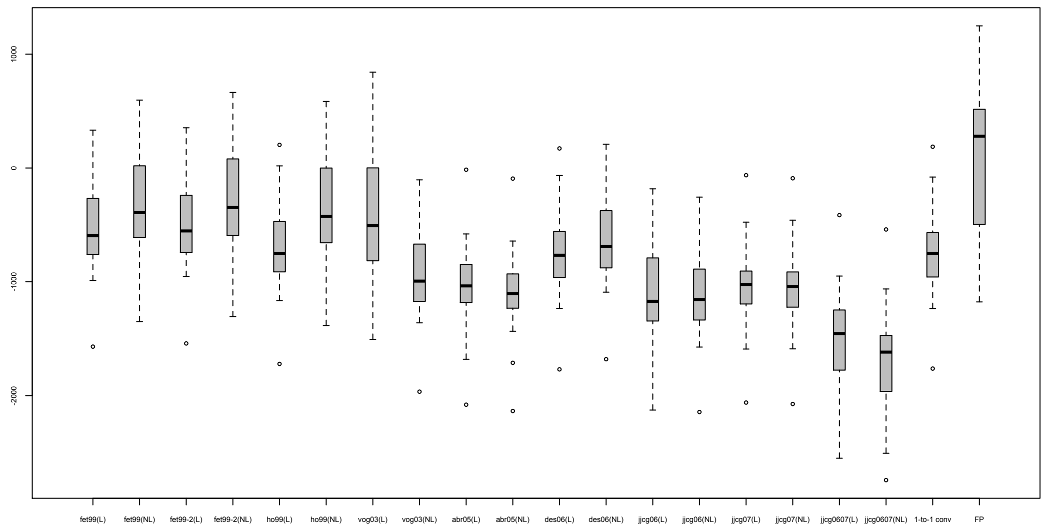


Figure 9: The boxplots of residuals obtained with 2SEP approach with the different conversion equations built using the data sets provided in [14], with the 1-to-1 conversion approach, and with the FP based estimation model

version equations provided in [75], and *1-1 Conv*. Indeed, in these latter cases the p-value of the Wilcoxon test was greater than 0.05 with a negligible or a small effect size.

As for the absolute residuals achieved in case of *internal(L)* and *internal(NL)*, we can observe that the performed test revealed statistically significant difference with the absolute residuals obtained with the FP based model (see Table 11). Thus, 2SEP using internal conversion equations allowed us to obtain significant better effort estimations than the FP based model.

4.5. Discussion

In our second empirical study we have assessed the accuracy of 2SEP and the results reported in Tables 10 and 11 revealed interesting but somehow contrasting results.

First of all we want to highlight that $1 - 1Conv$ does not work well for the application of 2SEP since there are several external FP $\rightarrow$ CFP transformations performing better. Thus, , the results we obtained with a of industrial Web applications, we can confirm the findings of the other studies, that the approach to just use Function Points without any conversion in a 2SEP leads to very poor estimations [14].

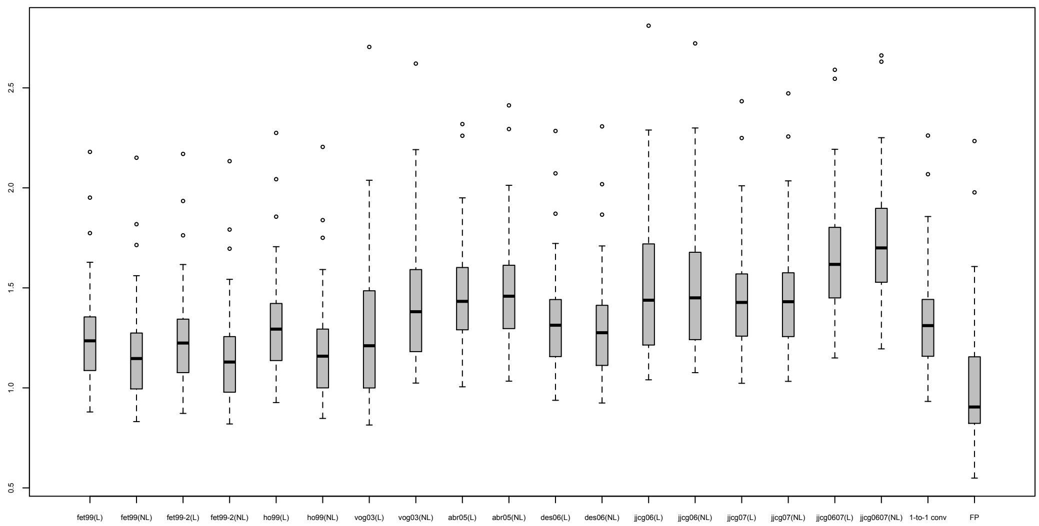


Figure 10: The boxplots of z obtained with 2SEP approach with the different conversion equations built using the data sets provided in [14], with the 1-to-1 conversion approach, and with the FP based estimation model

Another clear trend is that all the FP → CFP linear transformations employed with 2SEP using external conversion equations always lead to worse results than the FP based estimation model. The difference was statistically significant in all the cases, except for six (*fet99*, *fet99-2*, *ho99(L)*, *vog03(L)*, and *des06(L)* considering the data sets provided in [14] and *vanH07(L)* considering the data sets provided in [75]).

The results obtained with non-linear conversion equations are not conclusive. Indeed, in four cases (i.e., *fet99(NL)*, *fet99-2(NL)*, and *ho99(NL)* from [14] and *jjcg0607*(NL) from [75]) the effort estimates achieved with 2SEP were even better than those obtained with the FP based model, but the difference was not statistically significant. In six cases (i.e., *vog03(NL)*, *abr05(NL)*, *jjcg06(NL)*, *jjcg07(NL)*, and *jjcg0607(NL)* considering the data sets provided in [14] and *vog03(NL)* considering the data sets provided in [75]) the FP based model provided significantly better estimates than those achieved with the estimation models built with 2SEP. In the remaining cases, the difference was not significant in the absolute residuals obtained with the FP based model and with the estimation models built with 2SEP.

As for the internal conversion equations (both linear and non-linear ones), the results are better than those achieved with the FP based model.

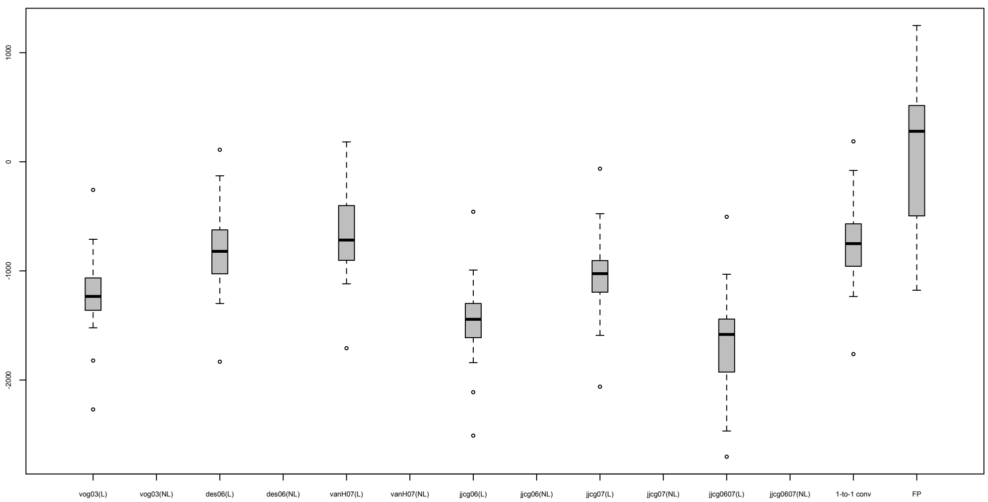


Figure 11: The boxplots of residuals obtained with 2SEP approach with the conversion equations provided in [75], with the 1-to-1 conversion approach, and with the FP based estimation model

To summarize, we can conclude that the choice of the FP $\rightarrow$ CFP conversion equation to be employed in 2SEP results to be crucial. In particular, we cannot positively answer $RQ2_a$, i.e., *Is the Web effort estimation accuracy obtained employing 2SEP, with (linear and non-linear) external conversion equations, not significantly worse than the accuracy achieved by exploiting FPs in models built with SLR?*, since 15 of the 31 considered external conversion equations provided significantly worse predictions than the FP based model, with 2SEP. On the other hand, we also cannot negatively answer $RQ2_a$, since for the remaining 16 external conversion equations the accuracy obtained employing 2SEP was not significantly worse (for 4 of them is even better) than the accuracy achieved by exploiting Function Points. Thus, the 2SEP approach using external conversion equations could potentially be exploited to carry out a smooth migration from FPA to COSMIC, nevertheless the choice of the FP $\rightarrow$ CFP conversion equation is crucial to get good results.

Differently, we can positively answer $RQ2_b$, i.e., *Is the Web effort estimation accuracy obtained employing 2SEP, with (linear and non-linear) internal conversion equations, not significantly worse than the accuracy achieved by*

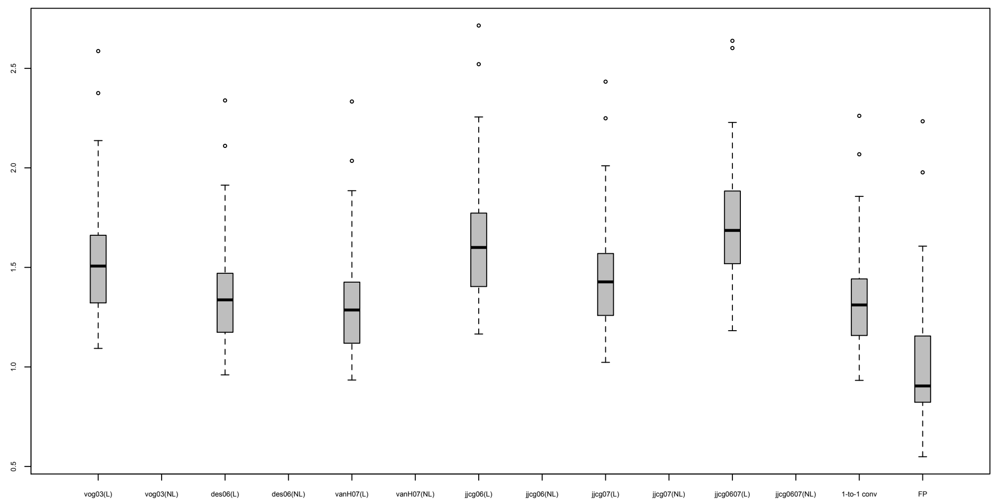


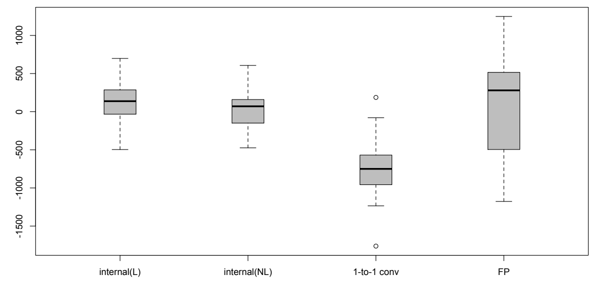
Figure 12: The boxplots of z obtained with 2SEP approach with with the conversion equations provided in [75], with the 1-to-1 conversion approach, and with the FP based estimation model

exploiting FPs in models built with SLR?, since both linear and non-linear equations allowed us to obtain a prediction accuracy better than the one achieved with the FP based model. So, the 2SEP approach with internal conversion equations can be effective to support the migration from FPA to COSMIC. The effort to remeasure a small sample set of applications (5 was effective in our study) is rewarded by a better accuracy.

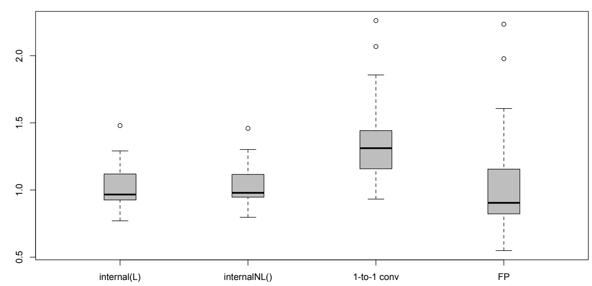
5. Threats to validity

It is widely recognized that several factors can bias the construct, internal, external, and conclusion validity of empirical studies [49].

As for the construct validity, the choice of the size measures and how to collect information to determine size measures and actual effort represent a crucial aspect. Regarding the selection of the approach to size the Web applications, we employed (IFPUG) FPA and COSMIC that represent examples of first and second generations of FSM methods. Thus, the number of FPs and of CFP were calculated as measure of the Web application size. Often, the collection of information about the size measures and actual ef-



(a)



(b)

Figure 13: The boxplots of residuals (a) and z (b) obtained with 2SEP approach with internal conversion, with the 1-to-1 conversion approach, and with the FP based estimation model

fort represents the main difficulty to carry out this kind of study [78]. As described in Section 3.1.1 we have supervised the procedure employed by the involved software company to carefully collect the information we needed for the empirical analysis. In particular, we tried to perform the data collection task in a controlled and uniform fashion. Of course we have to take into account that empirical studies do not ensure the level of confidence achieved with controlled experiments.

Some factors should be taken into account for the internal validity: subjects' authoring and reliability of the data and lack of standardization [12] [49] [60]. The managers involved in the study were professionals who worked in the software company. No initial selection of the subjects was carried out, so no bias has been apparently introduced. Moreover, the Web applications were developed with technologies and methods that subjects had experienced. Consequently, confounding effects from the employed methods and tools should be excluded. As for the reliability of the data and lack of standardization, the used questionnaires were the same for all the Web applications, and the project managers were instructed on how to fill them in, to correctly provide the required information. Instrumentation effects in general did not occur in this kind of studies.

As for the conclusion validity, we carefully applied the estimation methods and the statistical tests, verifying all the required assumptions.

With regard to the external validity, we are confident that the type of the analyzed Web applications did not bias the validity of the achieved results, since for their functionalities, target platforms, and complexity they can be considered representative samples of current Web applications. Another threat could be related to the fact that we considered Web applications from one company. To the best of our knowledge, there is only one data set that contains (Web and non-Web) applications from different company, i.e., ISBSG. However, in our analysis we were interested in analyzing the experience of a single company developing Web applications.

On the other hand, it is recognized that the results obtained in an industrial context might not hold in other contexts. Indeed, each context might be characterized by some specific project and human factors, such as development process, developer experience, application domain, tools, technologies used, time, and budget constraints [79].

6. Conclusions

Functional Size Measures are the typical choice for management tasks like estimating a software project development effort, since they can be applied on the Functional User Requirements. Many FSM methods have been proposed in the last decades, that can be distinguished in 1^{st} (e.g., FPA) and 2^{nd} (i.e., COSMIC) generations. To the best of our knowledge, there is no empirical comparison of COSMIC performances with respect to 1^{st} generation methods, such as FPA, for Web effort estimation. This is also probably due to the lack of suitable industrial data sets containing information on Web application measured with both FPA and COSMIC. The main goal of our work was to empirically investigate whether COSMIC is more effective than FPA for Web effort estimation, thus motivating the migration from 1^{st} generation FSM methods to the 2^{nd} one. We were also interested in investigating the effectiveness of an approach to facilitate the migration from FPA to COSMIC. Companies could apply a two-step estimation process (2SEP) that exploits historical FPA data and a conversion equation to estimate COSMIC sizes and use them to predict development effort, until enough COSMIC data has been collected. In the case they would not spend effort and time in resizing historical projects in terms of COSMIC, to be used for effort estimation, they could employ external conversion equations, otherwise they could remeasure a small sample data set in terms of COSMIC and build an internal conversion equation.

We performed two empirical studies, both exploiting data from 25 industrial Web applications, and employing leave-one-out cross validation as validation method.

The results of the first empirical study revealed that COSMIC outperformed Function Points as indicator of development effort by providing significantly better estimations, when used in combination with two different estimation techniques (SLR and CBR). Thus, for the software company involved in our empirical study, the decision of migrating from FPA to COSMIC is positively supported by the results of the study presented here.

The results of the second empirical study revealed that the 2SEP approach could potentially be exploited to carry out a migration from FPA to COSMIC. Anyhow, the choice of the FP $\rightarrow$ CFP conversion equation is crucial to achieve good results. As expected, the internal conversion equations allowed us to obtain effort predictions better than those achieved employing external conversion equations. However, employing internal conversion equations requires re-measuring a sample of previous developed applications, i.e., further effort by managers of the company. As for external conversion equations, more investigations should be carried out to identify more accurate conversion equations possibly relating them to specific types of software systems.

The experimental results presented herein hold for the company involved in our study and they should be assessed on further data as soon as it becomes available. We have planned to collect information from other companies, operating also in other industrial contexts, in order to compare the accuracy of COSMIC and FPs for Web effort estimation and assess a two-step process for building effort estimation models.

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