

Estimation Models based on Functional Profiles

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Abstract

A functional profile provides information about the distribution of functionality within specific software and permits comparison of its functional distribution with that of a sample of projects. This study investigates the impact of functional profiles on effort estimation models and compare results with estimation models based only on total functional size. The data set used in this study includes the projects from the International Software Benchmarking Standards Group (ISBSG) repository that have had their functional size measured with COSMIC-FFP, the ISO 19761 standard.

Keywords: COSMIC-FFP, ISO 19761, estimation models, functional profiles

1. Introduction

In software engineering, it is widely accepted that software size is among the key factors impacting productivity, and plays an important role in estimation models [1]. While software size was initially measured mostly in lines of codes, a new type of sizing method, Function Point Analysis (FPA) [2], was developed in the late 1970s based on the measurement of the functional user requirements. From the mid 1980's on, numerous variants of FPA appeared next and then, in the early 2000s, COSMIC-FFP as a second-generation functional sizing method [3,4].

There is now a large body of literature on the use of functional size for developing software estimation models; however, while most authors have built estimation models based on total functional size only, virtually none of these authors has investigated the size-effort relationship based on a software functional profile.

The concept of a software functional profile is defined in [5,6] as the distribution of function types within the software. This concept can be measured using existing functional size measurement methods by taking into account the types of base functional components (BFC – ISO 14143-1 [7]) – commonly referred to as ‘function types’, defined in each functional size measurement method.

For each of these functional sizing methods, the total functional size is obtained by adding the size of each of their corresponding function types; for instance, FPA has five function types (External inputs - EI, External outputs - EO, External Enquiries - EQ, Internal Logical Files - ILF and External Interface

Files - EIF) while COSMIC-FFP has four (Entries-E, Exits-X, Reads-R and Writes-W). In practice, the distribution of function types will vary across each software being measured, with more or less variations.

For the COSMIC-FFP method [3,4], adopted in 2003 as ISO 19761, a functional profile corresponds to the relative distribution of its four function types for any particular project; that is, the percentages of Entries, Exits, Reads and Writes (E%, X%, R% and W%).

Such a functional profile provides information about the distribution of functionality within specific software and permits comparison of its functional distribution with that of a sample of projects for which the average functional profile is known, as well as its dispersion across such an average, in terms, for example, of standard deviation, skewness and kurtosis.

Subsequent analysis can then take this functional profile into account in building estimation models, in addition to other variables, such as the development language, the logical and physical architecture (core architecture, development platform, tools, etc.) and the project context (project origin, project type, development methodology, etc.).

This paper reports on an analysis of the impact of the functional profile on project effort using data from the International Software Benchmarking Standards Group (ISBSG) repository [8]. The ISBSG projects included in this analysis have all been sized with the COSMIC-FFP method.

This paper is organized as follows: Section 2 presents the related work. Section 3 presents the data preparation and the methodology for building the regression models taking into account various aspects of a project functional profile. Section 4 presents the various regression models built, and their results. Finally, a summary is presented in Section 5.

2. Related work

2.1. FPA Functional Profiles

Abran *et al.* [5] used the 2003 version of the ISBSG repository to build estimation models for the projects for which functional size was measured with the FPA method. In this 2003 study, a functional profile of a project is defined as its set of the five types of FPA functions, each expressed as a percentage (i.e. the set of EI%, EO%, EQ%, ILF%,

EIF%), and the functional profile of a sample as the weighted average of the functional profiles of each project member of the sample. Abran *et al.* [5] investigated whether or not the size-effort relationship was stronger if a project was close to the average profile of the sample studied. The 2003 ISBSG data were divided into three samples (software written in COBOL, NATURAL and C), each sample containing over 30 projects. When the functional profiles were calculated and analyzed for each of the three samples, it was observed that about 80% of projects were located within a range of $\pm 30\%$ of the average functional profile for the COBOL and NATURAL samples, and within a range of $\pm 20\%$ for the C sample.

Next, each sample was divided into two sets: projects which were close to the average functional profile (e.g. within the ± 30 or 20% range of the average functional profiles respectively) and the projects that were farther from the average profile and therefore outside these ranges. For each of these sets, regression models were built using linear least-square regression using either the total FPA size as the independent variable, or, alternatively, each of the five FPA functional types:

- For each sample, it was noted that there was one function type that had a stronger relationship with project effort;

- The sets of projects located within a certain range of the average profile led to estimation models similar to that for the average profile, whereas the projects located outside the range gave different regression models and these were specific to each of the corresponding subsets of projects.

Since the functional profile of a project can be identified right at the requirements phase, a functional profile can be identified very early on in the life cycle, at which point the model to use for estimation purposes can be selected.

2.2 Alternative techniques

Djellab [6] proposes other techniques for determining functional profiles of the set of 145 development and enhancement projects reported in Kitchenham's study [7]. For instance, the average frequencies are calculated for each of the five types of function, and the function type with the highest average is then selected as the dominant function type for splitting the samples. Another technique used in [6] is to consider simultaneously the most common frequencies within each of the function types.

3. Methodology: Data Preparation and Building Regression Models

The purpose of this research project is to study the relation between the effort and the functional profile of projects sized with the COSMIC-FFP method. The available data set contains the 96 projects sized with COSMIC-FFP and included in the February 2006

version of the International Software Benchmarking Standards Group (ISBSG) repository [8].

The research methodology used consists of two phases:

- Data preparation
- Building of regression models

3.1. Data preparation

A number of data points had to be deleted from the set of 96 COSMIC-FFP projects for the following reasons:

- 5 had poor data quality, as rated by the ISBSG;
- Of the remaining 91 projects, 20 did not have the detail information sorted by function type.

The remaining 71 projects were then divided into three categories:

- A) Development projects with a single layer: 22 projects;
- B) Development projects with multiple layers: 24 projects;
- C) Enhancement projects with one or more layers: 25 projects.

The next step consisted in identifying and eliminating the obvious outliers on both the Effort and Functional Size variables; these outliers were deleted based on a graphical analysis [10,11]. The numbers of projects remaining in each sample are:

- Development projects with a single layer: 15 projects;
- Development projects with multiple layers: 17 projects;
- Enhancement projects: 18 projects.

In summary, 50 projects were retained for analysis, within the three categories above.

3.2. Building regression models

The construction of estimation models with regression analysis is achieved next, in three steps:

- 1- Regression models without considering the functional profile.
- 2- Regression models with the projects closer to the dominant profile within a function type. This involves the following sub-steps: identification of which of the four function types is most frequent in the sample (eg. dominant), calculation of the average contribution of this dominant function type in the sample and then building of estimation models by excluding about 20% of the projects that are farther away from this average within a sample (eg. functional outliers).
- 3- Regression models with projects within the most common frequencies for all functions. This involves the following sub-steps: identification of the frequency distribution for each function type, identification of the ranges of most common frequency and then identification of the projects that simultaneously fall within the most common frequencies for each function type. Projects within a sample that then meet simultaneously all of

these most common ranges of frequencies are then selected for building estimation models.

4. Regression models

4.1. Projects without consideration of their functional profile

The first analysis does not take into account the information about the functional profile. Figures 1 to 3 present both the samples and the linear regression models built with these samples. The coefficients of determination (R^2) and the regression equations are also presented underneath each figure. The number of data observations in each sample is included in parantheses (eg. N=..) at the end of the title of each figure.

In all of the figures, the x axis represents the functional size expressed in COSMIC-FFP units (eg. Cfsu: COSMIC functional size unit) and the y axis represents the effort expressed in hours.

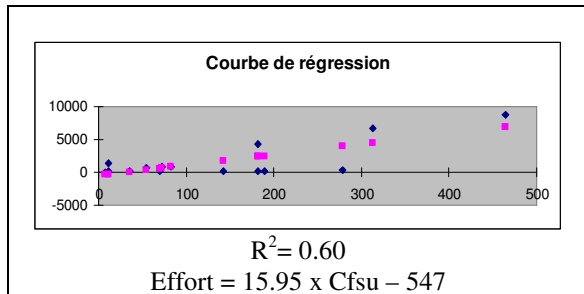


Figure 1: Development projects - 1 layer (N=15)

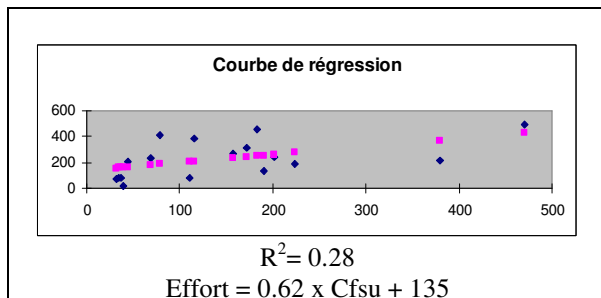


Figure 2: Development projects - multiple layers (N=17)

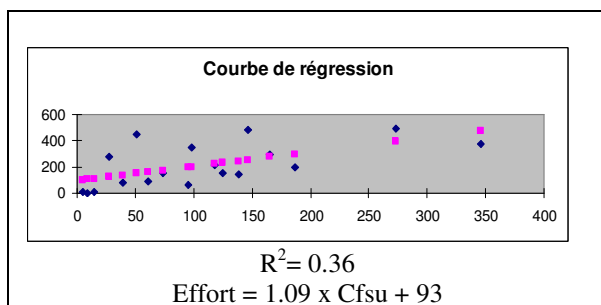


Figure 3: Enhancement projects (N=18)

A summary of the results of these regression models is presented in Table 4. For these three samples only the set of development projects with a

single layer (Figure 1) leads to an estimation model with a reasonable coefficient of determination (R^2) of 0.60.

In Figure 1 it can also be observed that projects within the 100 to 300 Cfsu size range are not well estimated by the regression model. For the other two samples, the regression models are poor with coefficients of determination (R^2) of 0.28 and 0.36.

Table 4: Regressions models – without consideration of functional profile

Sample			
	No. of projects	R^2	Effort
Development Projects– 1 layer	15	0.60	15.95 Cfsu – 547
Development Projects – multiple layers	17	0.28	0.62 Cfsu + 135
Enhancement Projects	18	0.36	1.09 Cfsu + 93

4.2. Projects close to the dominant function type

The second stage of the analysis is performed by first identifying the dominant function type (E, X, R, W) in each of the three samples (eg. with the greatest frequency distribution).

For the set of development projects with a single layer (Table 2), it is the Exit function type that is dominant among the four function types; for the set of development projects with multiple layers (Table 3), the Entry and Exit are both dominant, while for the set of enhancement projects (Table 3), it is the Read function type that is dominant.

For each of the three samples, the weighted average frequency of their respective dominant functional frequency is calculated next.

Each of these three samples is subdivided next into two subsets, one that would contain about 80% of the projects (e.g. the 80% of the projects that are relatively close to the average frequency), and another containing about 20% of the projects (e.g. the 20% of the projects that lie considerably far from the average frequency, and that could be considered as functional outliers within these samples).

In practice, the size of the subsets will not be exactly 80/20% and will vary. For instance:

- For the development projects with a single layer, it was found that 73% of the projects were within a +/- 75% range of the average of its dominant Exit function type (Table 2): 11 projects fall within +/- 75% of the weighted average Exit function types, and 4 farther from it (these 4 projects are then considered as functional outliers within this sample).
- For the development projects with multiple layers, 88% are within +/-50% of the average of its

dominant Entry function type – Table 3: 15 projects fall within +/- 50%, and 2 farther.

- For the enhancement projects, 77% are within +/- 40% of the average of its dominant Read function type – Table 4: 14 projects fall within +/- 40%, and 4 farther.

Then, the regression models are built for the projects within that threshold (Figures 4 to 6). For instance, for the development projects with a single layer, 11 projects fall within +/- 75% of the weighted Exit function types, and the corresponding regression model has a coefficient of determination (R^2) of 0.83 (table 2 and figure 4); this is a significant improvement over the R^2 of 0.60 in Figure 1 (which did not take into account any aspect of the functional distribution for each project in the sample).

Table 2: Development projects – 1 layer	
Dominant function type	Exit
Percentage of projects within a range of $\pm 75\%$ of the average of the dominant Exit function type	73%
Number of projects within the $\pm 75\%$ range	11
Number of projects outside the $\pm 75\%$ range (eg. Functional outliers)	4
Model for projects within the range	$R^2=0.83$

Table 3: Development projects – multiple layers		
Dominant function type	Entries	Exits
Percentage of projects within the dominant selection and range	88%	76%
Range across the average of the dominant function type	$\pm 50\%$	$\pm 60\%$
Number of projects within the range	15	13
Number of projects outside the range (functional outliers)	2	4
Model- projects within range - R^2	0.28	0.22

Table 4: Enhancement projects	
Dominant function type	Reads
Percentage of projects within a range of $\pm 40\%$ of the average of the dominant Read function type	77%
Number of projects within the $\pm 40\%$ range (eg. Functional outliers)	14
Number of projects outside the range	4
Model for projects within the range	$R^2=0.60$

For multi-layer development projects (table 3), it is the subset based on the Entry function type that provides the best R^2 ; consequently, the next analysis focuses on this subset only. Table 5 summarizes the results of the regression models for each sample using

their respective dominant function type, and excluding their functional outliers. A comparison with table 1 (without consideration of functional profile) shows that a greater coefficient of regression (R^2) is observed for both the single-layer development and for the enhancement samples. For the development projects – multiple layers sample without a single dominant function type, this approach does not improve its estimation model.

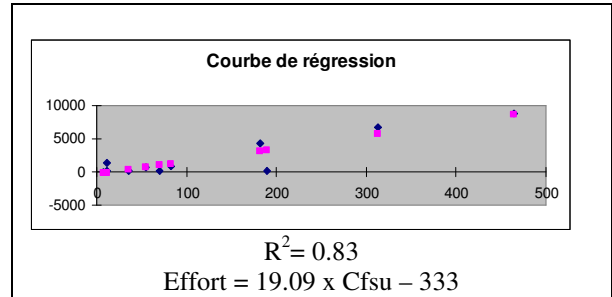


Figure 4: Development projects – 1 layer (N=11)

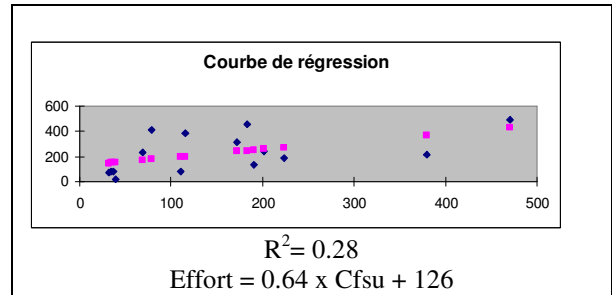


Figure 5: Development projects – multiple layers (N=15)

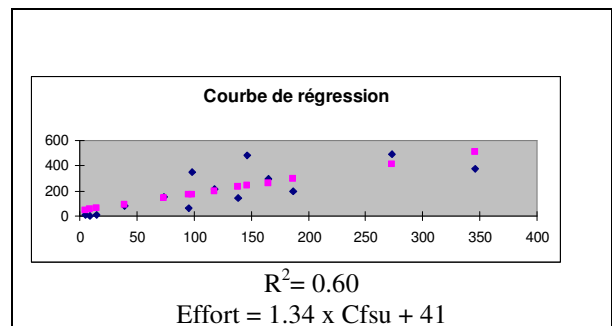


Figure 6: Enhancement projects (N=14)

Table 5: Regression models – Dominant function type (excluding functional outliers)

Sample	No. of projects	R^2	Effort
Development projects – 1 layer	11	0.83	19.09 Cfsu – 333
Dev. projects – multiple layers	15	0.28	0.64 Cfsu + 126
Enhancement projects	14	0.60	1.34 Cfsu + 41

4.3. Projects within most common frequencies for all function types

The Excel FREQUENCY function was used to calculate the distribution of the frequencies for each function type.

4.3.1 Development projects –1 layer

The frequency graphs for each function type are presented in figure 7 for the sample of 15 development projects with a single layer. The x axis represents the percentage of the function type, and the y axis represents the number of projects with this % of function type. It can be observed that, while there is only one frequency peak for the Entry function type, there are two frequency peaks for the other three function types.

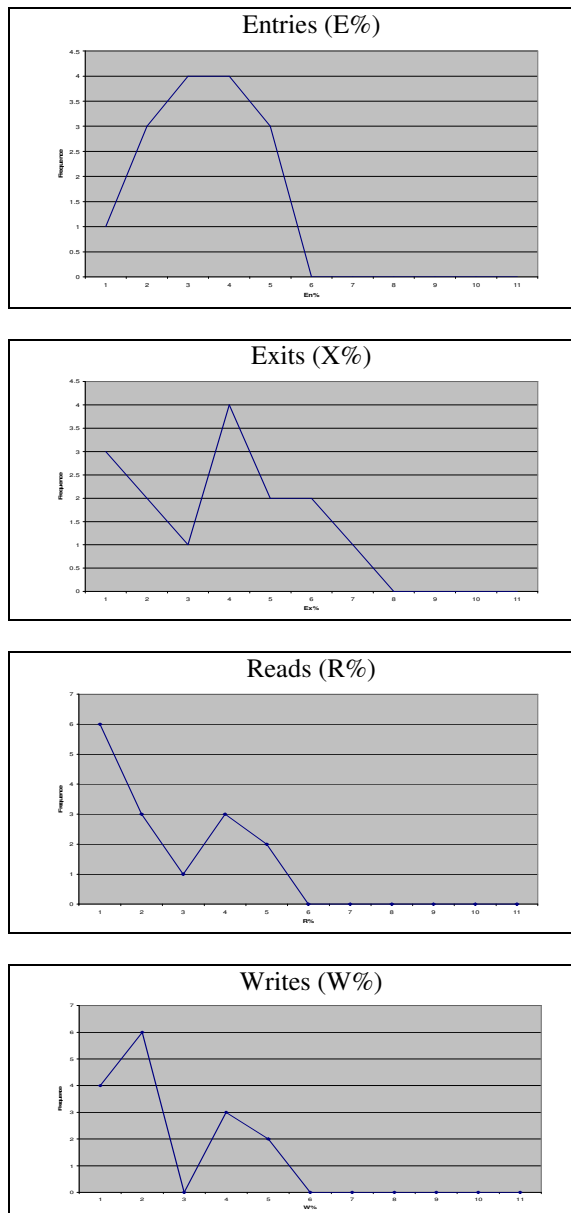


Figure 7: Frequency graphs of function type – Development - 1 layer (N=15)

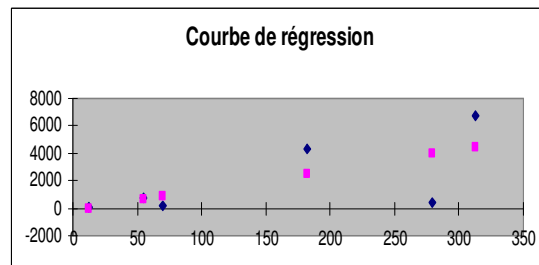
The most common frequency ranges for each function type in Figure 7 are listed in shaded cells in Table 6.

Table 6: Most common frequency ranges by function type – Development - 1 layer

	0-5%	6-20%	21-30%	31-50%	51-55%
Entry%					
Exit%					
Read%					
Write%					

In this sample, only 6 projects meet simultaneously all of these most common functional ranges (eg. the double set of ranges: [6%,20%] and [31%,50%]).

The regression model for these 6 data points is presented in Figure 8.



$$R^2 = 0.44$$

$$\text{Effort} = 14.83 \times \text{Cfsu} - 182$$

Figure 8: Regression model - within the most common frequency ranges – 1 layer (N=6)

4.3.2 Development projects – multiple layers

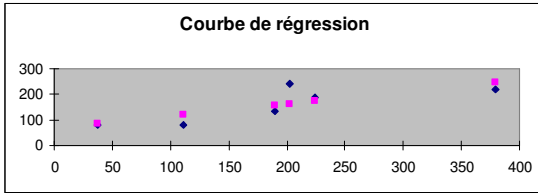
The frequency graphs per function type for the 17 multiple-layer development projects are presented in Figure 9.

The most common frequency ranges for each function type in Figure 9 are listed in shaded cells in Table 7.

Table 7: Most common frequency ranges by function type – multiple layers (N=17)

	5	10	15	20	30	35	45	55	75
En%									
Ex%									
R%									
W%									

In this sample, only 6 projects meet simultaneously all of these functional ranges. The regression model for these 6 data points is presented in Figure 10.



$$R^2 = 0.61$$

$$\text{Effort} = 0.47 \times \text{Cfsu} + 66$$

Figure 10: Regression model - within the most common frequency ranges – multiple layers (N=6)

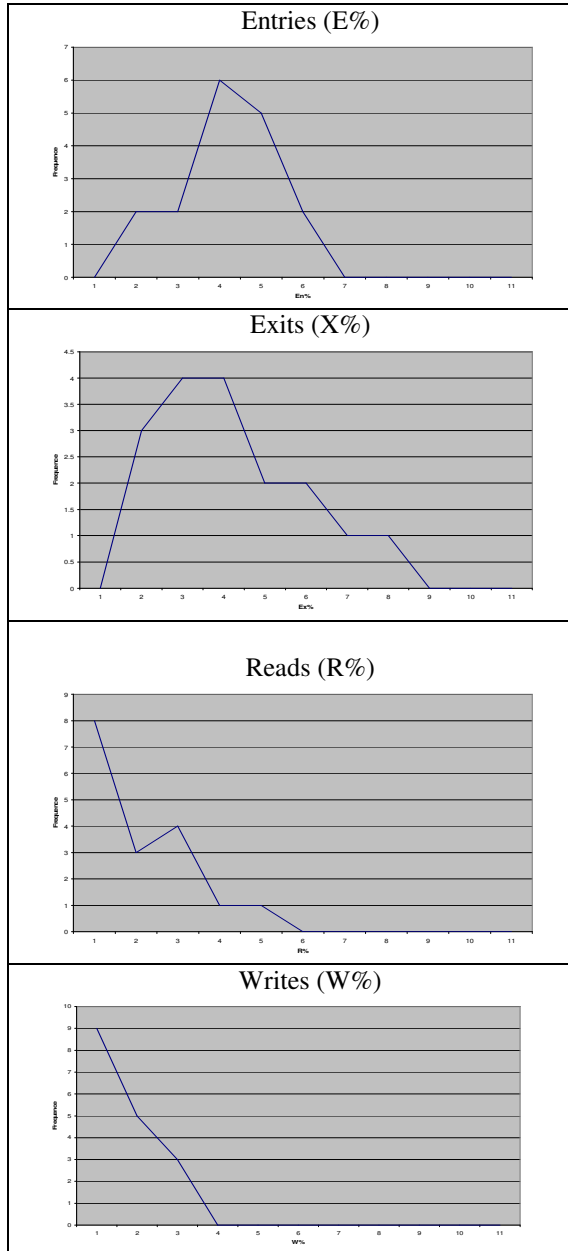


Figure 9: Frequency graphs of function type, by function type – multiple layers (N=17)

4.3.3 Enhancement projects

The frequency graphs for the 18 enhancement projects are presented in figure 11, per function type.

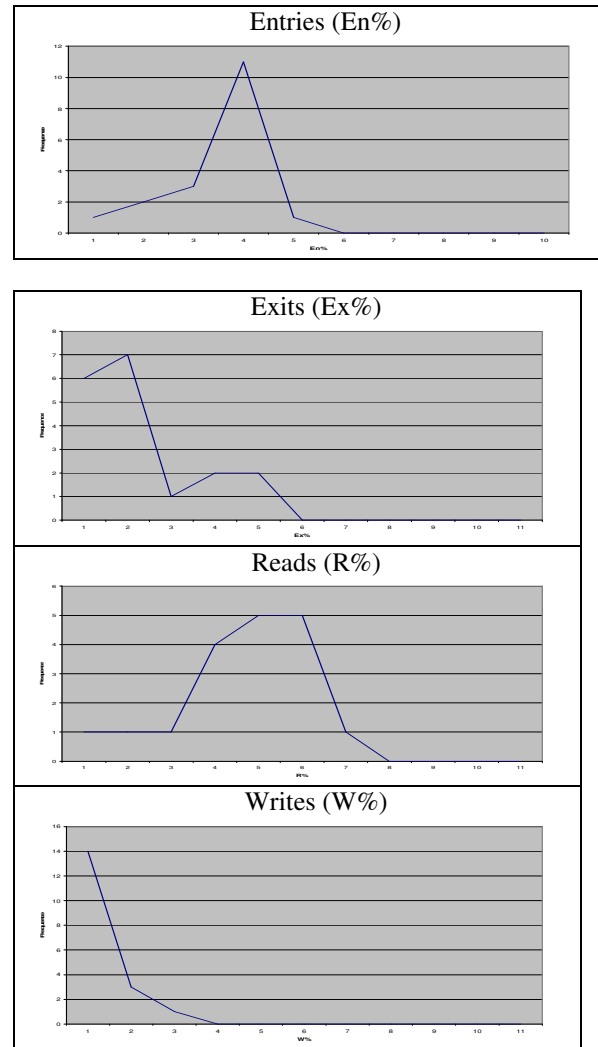


Figure 11: Frequency graphs of function type, by function type – Enhancements (N=18)

The most common frequency ranges for each function type in Figure 11 are listed in shaded cells in Table 8.

Table 8: Most common frequency ranges by function type – Enhancements (N=18)

	5	20	25	30	45	50	65
En%							
Ex%							
R%							
W%							

In this sample, only 10 projects meet simultaneously all of these functional ranges. The regression model for these 10 data points is presented in Figure 12.

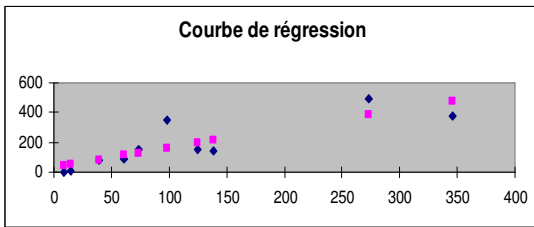


Figure 12: Regression model - within the most common frequency ranges – enhancements (N=10)

4.3.4 Summary

A summary of the results of the regressions models in this 4.3 section is presented in Table 9. This shows that for two instances (development projects – multiple layers and Enhancement projects) the projects that meet simultaneously the most common frequency ranges by function types lead to better estimations (eg. better R^2) when compared to the results from table 1. This represents a significant improvement over the models not taking into account the functional profile; on the other hand, only a few projects qualify as meeting all conditions, thereby limiting the generalization power of this finding.

Table 9: Regressions models – Projects within the most common frequency ranges

Sample			
	# projects	R^2	Effort
Development projects – 1 layer	6	0.44	14.83 Cfsu – 182
Development projects – multiple layers	6	0.61	0.47 Cfsu + 66
Enhancement projects	10	0.72	1.27 Cfsu + 35

5. Summary

This research work has investigated the impact of the functional profiles on effort estimation models for projects for which functional size was measured with COSMIC-FFP – ISO 19761. The data set includes projects from the ISBSG repository that have had their functional size measured with COSMIC-FFP, the ISO 19761 standard. These projects were divided into three samples based on the following characteristics:

- Development projects – 1 layer
- Development projects – multiple layers
- Enhancement projects

Outliers on the two variables (size and effort) were next excluded.

For the estimation models built with these samples, the findings can be summarized as follows.

- Only the sample of development projects with a single layer has a reasonable coefficient of regression ($R^2 = 0.60$) for the corresponding 15 projects, but with a rather large error for the

projects of size higher than 100 Cfsu – See table 1.

- For the projects that are not outliers with respect to the dominant function type of their sample, two samples have much better coefficient of regression (Sample 1: development projects with a single layer and sample 3: Enhancement projects) – see table 5.
- For the projects that are simultaneously within the ranges of the most frequent frequencies for all function types, two samples have much better coefficient of regression (Sample 2: development projects with multiple layers and sample 3: Enhancement projects) – see table 9.

From these analyses, it can be observed that the identification of the functional profile of a project and its comparison with the profiles of their own samples can help in selecting the best estimation models relevant to its own functional profile.

What is of particular interest is that this model selection process is possible for estimation purposes, since the functional size of a project can be measured and identified early on in the project life cycle, and that the specific functional distribution of a project can be compared to those in a data base of projects measured with the same sizing technique. The outcome of the comparison can then be used as a basis for selecting which of the available models to use for this particular project that needs to be estimated.

It must be stressed, however, that the samples are still relatively small for statistical significance, and one should not yet generalize the findings. Similarly for projects that could be considered as functional outliers with respect to their corresponding samples, there are simply too few of them for meaningful statistical analysis.

Replicated studies should be conducted when more of projects become available in the ISBSG repository. Similarly, when more projects become available, additional productivity factors could be taken into account in the regression models, as well as refinement of variables such as effort as discussed in [12].

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