Convertibility of Functional Size Measurements: New Insights and Methodological Issues

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ABSTRACT

Objective: Most of the models and tools currently used for effort estimation require in input the measure of the functional size of the program to be developed. In particular, Function Points (FP) are most often used for estimation purposes. However, several organizations are considering to move from Function Point Analysis (FPA) to the COSMIC functional size measurement method, mainly because the latter is more easily and generally applicable than FPA. However, moving from FPA to COSMIC implies that the experience bases funded on function points become unusable. This paper explores the quantitative relations between FPA and COSMIC measures and elements, in view of the transformation of FP into COSMIC Function Points (CFP) and vice versa.

Methods: The paper considers the data from 25 projects and analyses the relations that link the base functional components (BFC) of FPA and COSMIC. With respect to previous studies that addressed only the relations between the different functional size measures, the paper investigates the dependencies of FP and CFP from both FPA and COSMIC base functional components.

Results: In all the examined cases it was found that strong correlations exist between the considered measures.

Conclusions: The results found tend to suggest that in presence of a set of projects that are quite homogeneous –with respect to the application domain, the nature of computation performed, and the implementation technology– it is possible to obtain fairly precise estimations of the functional size (expressed either in FP or in CFP) on the basis of a few BFC.

Categories and Subject Descriptors

D.3.3 [**Software Engineering**]: Metrics – *product metrics.*

General Terms

Measurement, Management, Economics.

Keywords

COSMIC Function Points, Function Point Analysis, functional size measurement, functional size measure convertibility.

1. INTRODUCTION

Most of the models and tools currently used for effort estimation require the measure of the functional size of the program to be developed as input: for instance COCOMO II [16] accepts the functional size in Function Points as input. In particular, Function Points (FP) [1][2] are most often used for estimation purposes. However, several organizations are considering to change their functional size measurement method from Function Point Analysis (FPA) to COSMIC [3], mainly because the latter is more easily and generally applicable than FPA. However, moving from FPA to COSMIC implies that the experience bases funded on function points become unusable. This paper explores the quantitative relations between FPA and COSMIC measures and elements, in view of the transformation of FP into COSMIC Function Points (CFP) and vice versa.

The work presented here aims at overcoming a few limitations of the approach adopted by most of the studies concerning the correlation between CFP [3] and traditional (IFPUG [1][2], NESMA[7][5], etc.) function points. In fact, previous studies (see for instance [4], [13], [14] and [10]) tend to concentrate exclusively on the relation between CFP and FP, without taking into account the contribution of the base functional components. The consequence is that questions like "*why is the correlation between FP and CFP this high?*" [4] remain without a convincing answer.

This paper takes as a representative example of the previous studies the work by van Heeringen [4]. In that work, a set of projects is considered (see Table 1) and the correlation between COSMIC function points and NESMA function points is studied[1]. In this paper, the data reported in Table 1 are further analyzed, in order to extract additional knowledge about the correlation that may exist not only between Function Points and COSMIC Function Point, but also between such measures and the BFC.

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[1] For the purpose of this paper the differences between NESMA FP and other types of FP, e.g., IFPUG ones, is negligible. Differences lay mainly in the way "code tables" are counted in the two approaches. The numerical difference is however very small, also according to van Heeringen [4].

In particular, the paper redefines the scope of the investigation according to the very goals that drive these studies. In fact, the main reason for looking for a correlation between CFP and FP is that such correlation could lead to a convertibility model that lets us use effort estimation models that incorporate the knowledge of productivity in terms of FP/PersonMonths. To this end, we have two possibilities:

– Estimate the number of FP on the basis of the counted CFP and apply a traditional method –like COCOMO [16]– that requires function point as input.
– Convert productivity data expressed in FP/PersonMonth into CFP/PersonMonth and apply these productivity data to the measure of CFP.

This situation –due to the fact that currently not enough historical data are available to derive a function that links the development effort to the size in CFP– calls for the ability to convert CFP into traditional function points, and vice versa.

Since we are interested in finding a relation that lets us estimate function points on the basis of CFP, we should be even more interested in finding a function that provides the number of function points given only some COSMIC BFC, like for instance the number of functional processes. In fact, it is quite clear that if such function existed, we could just measure the number of functional processes (which is a fairly easy and fast task), convert such number into FP, and use the size in FP to estimate the development effort.

Accordingly, the paper reports the analysis of a few correlations. In particular, the study concerned:

– Correlations between FP and COSMIC BFC;
– Correlations between CFP and FPA BFC;
– Correlations between FP and FPA BFC;
– Correlations between CFP BFC and FPA BFC.

The rest of the paper is organized as follows: Section 2 discusses the definition of both FP and CFP in terms of base functional components; illustrates the measurement processes and shows how simplifications in the computation of FP and CFP could simplify such processes and, consequently, the whole estimation process. Section 3 reports the data set from [4] and illustrates some data quality criteria that lead to the exclusion of a project's data. Section 4 illustrates the analysis performed and the results obtained. Section 5 discusses the generality of the results; Section 6 accounts for related work, while Section 7 draws some conclusions.

2. Functional Size Measurement Methods and Procedures

This section provides the background of the work: it briefly illustrates the COSMIC and FPA methods and measurement processes, and sketches the practical applications of the results of the analysis described in Section 4.

2.1 Function Point Analysis

According to FPA, the total size of the system is given by the sum of the number of Function Points contributed by the following base functional components (see Figure 1):

– Internal Logic Files (ILFs): the data managed by the system.
– External Interface Files (EIFs): the data managed by other applications/devices, and read by the system being measured.
– External Inputs (EIs): the processes whose main purpose is to update the data managed by the system.
– External Outputs (EOs): the processes whose main purpose is to perform some elaboration and provide results to the user or to external devices or systems.
– External Enquiries (EQs): the processes whose main purpose is to retrieve data from the system.

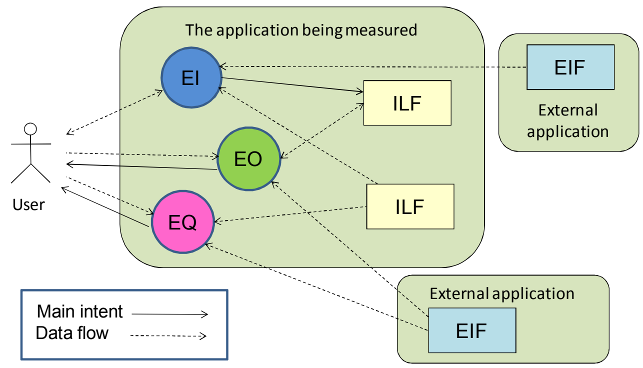

Figure 1. A schematic view of FPA base functional components.

ILF and EIF are called 'data functions': they are groups of logically related data that are meaningful to the users. EI, EO, and EQ are named 'transaction functions'; they are 'elementary processes', which are defined by the FPA as the smallest units of activity that are meaningful to the user(s). An elementary process must be self-contained and leave the application being counted in a consistent state.

All the data and transaction functions contribute a number of function points according to their "complexity". The complexity of ILFs and EIFs depends on the types of information contained (RET) and on the number of elementary pieces of information contained (DET). The complexity of transaction functions is determined by the number of ILFs and EIFs used (FTR), and the amount of elementary information (DET) that crosses the boundaries of the application.

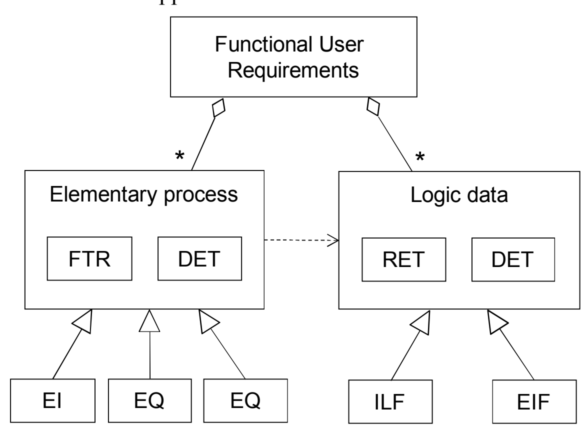

Figure 2. The model of FUR according to FPA.

Figure 2 illustrates schematically (in UML) how Functional User Requirements (FUR) are viewed according to FPA.

The work to be done in order to count Function Points is schematically illustrated in Figure 3. It is interesting to note that the upper part of the process is done at the level of FUR, i.e., you have to scan the FUR and identify elementary processes and logic data. This is a not very time consuming task, because the number of involved data and transaction functions is relatively small: consider for instance that the applications in our data set have an average of about 20 data functions and about 80 transaction functions. On the contrary, the bottom part of the process is much more demanding in terms of time and effort. In fact, you have to analyse each data and transaction function, and understand its internal organization, the final goal being to identify and count RET, DET and FTR. The job takes some time and effort, since you may have several (even tens) of RET and DET for every data function, and FTR and DET for every transaction function.

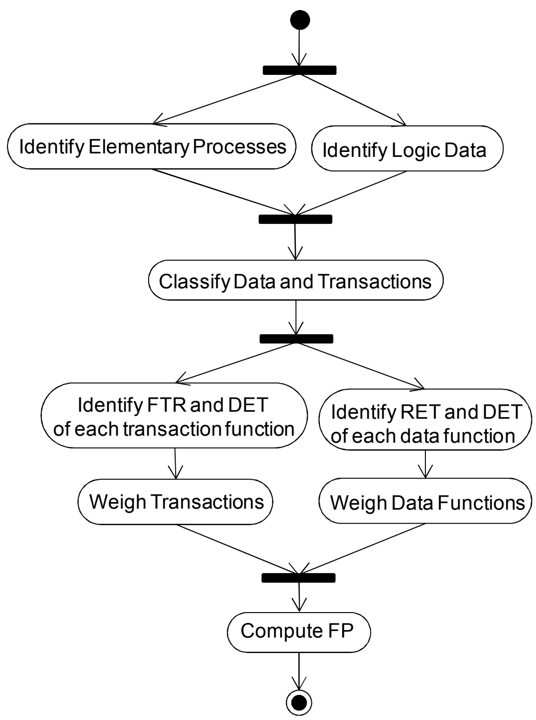

Figure 3. The FP measurement process (core).

2.2 COSMIC

The COSMIC measurement [3] applies to the Functional User Requirements of a given piece of software. The result is a number representing the functional size of the piece of software in COSMIC Function Points (CFP).

The COSMIC FSM method can be applied to the whole system as described in the FUR, or to a given component in a single layer. The former measure corresponds to the functional sizing of the application performed by FPA, the latter allows the user to measure only the relevant parts of the software. Throughout this paper only the end user measurement viewpoint is used, in order to make CFP comparable with FP (according to FPA, the boundary of the application to be measured is determined uniquely on the basis of the user's point of view). The functional users of the software are identified as the senders and/or intended recipients of data. Both human users and devices can be regarded as functional users.

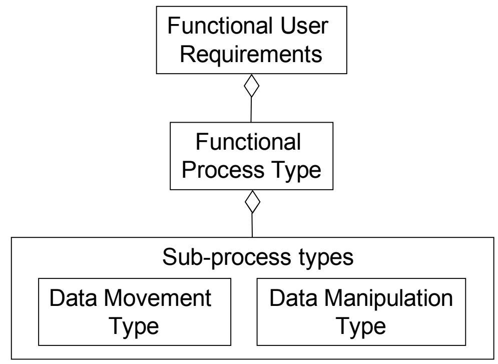

Figure 4. The COSMIC model of FUR.

The functionality of the software is measured according to the model of software illustrated in Figure 4. According to this model, the functional user requirements of a piece of software can be mapped into unique functional processes, triggered by a data movement from a functional user. Each functional process consists of sub-processes that can be either a data movement or a data manipulation. A data movement concerns a single data group, i.e., a unique set of data attributes that describe a single object of interest. In practice, the COSMIC data groups correspond to the FPA data functions, but are not counted directly, i.e., the existence of a data group does not contribute per se to the number of CFP.

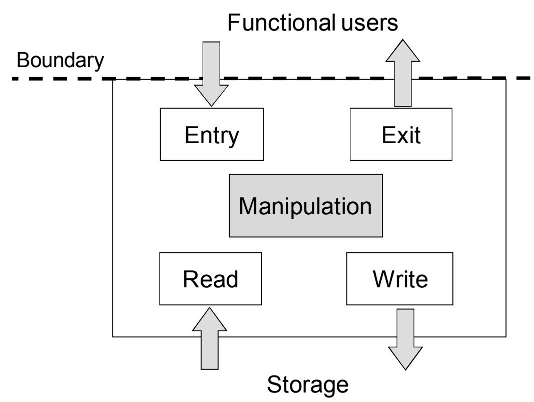

Figure 5. A schematic view of FPA base functional components.

There are four types of data movement (see Figure 5 [3]). An Entry moves a data group from a functional user into the software. An Exit moves a data group out of the software to a functional user. A Write moves a data group from the software to persistent storage. A Read moves a data group from persistent storage to the software. Note that the term "persistent storage" denotes data (including variables stored in RAM) whose value is preserved between two activations of the application's processes. Variables that store data that are meaningful only within a single instance of a process (e.g., temporary values, array indexes, etc.) are not considered persistent. Persistent storage is relevant with respect to the identification of Read and Write data movements, i.e., these data movements concern data groups persistently stored. On the contrary, Exit operations can concern 'transient' data groups, e.g., data that are created elaborating persistent data groups, but are not persistent themselves: they exist only to be communicated to a user.

In the current version of the COSMIC method data manipulation sub-processes are not measured; instead, the functionality of any data manipulation is assumed to be accounted for by the data movement with which it is associated.

The measurement proceeds as illustrated in Figure 6.

In the first step the functional processes and data groups are identified. Functional processes correspond to the functionalities that the system has to provide –according to the FUR– in response to the relevant events occurring in the world of the functional users. COSMIC data groups are similar to FPA logic data.

In the second step the data movements (Entries, Exits, Reads and Writes) of each functional process are identified. Each data movement involves data from no more than one data group. Every unique data movement contributes one CFP.

The final step just sums up the number of movements of all processes. In practice, for the COSMIC method the functional size of a piece of software is the number of its data movements.

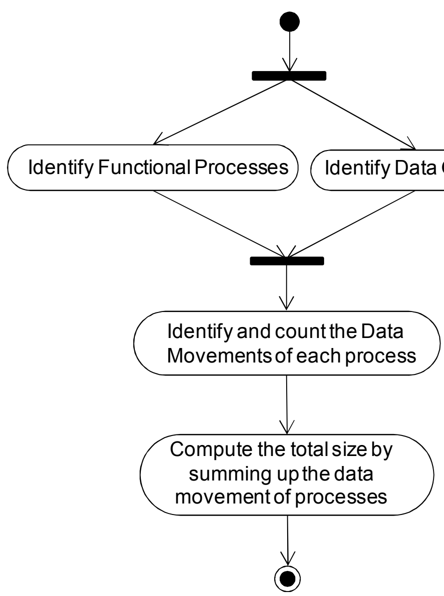

Figure 6. The COSMIC measurement process (core).

Also for the COSMIC measurement process we can note that the first step does not require much time and effort. In fact, identifying functional processes and data groups is quite similar to identifying data functions and elementary processes in FPA.

On the contrary, the identification of data movements has to be repeated for every functional process. Since we have several data movements per process, the job can take some effort. In our set of applications we have an average of 7 data movements per process: this means that the activity of identifying and counting the data movements is of one order of magnitude bigger than the former ones.

Anyway, it has to be noted that identifying data movements is generally easier than identifying FPA BFC, because data movements involve elements (the data groups) that have a coarser granularity than FPA DET.

2.3 The estimation process

Figure 7 shows a typical effort estimation process based on functional measures of size. Currently, hardly any reliable effort estimation model accepts CFP in input, because not enough historic data that correlate efforts to size in CFP are available; therefore, you have three possibilities:

- The measurement is done in FP and the estimation model accepts FP in input. This is a common case –since most effort estimation models accept FP in input– which does not require data conversion.
- The size is measured in CFP. The size in CFP is converted into a size in FP, which is used as an input to the effort estimation model.
- The size is measured in CFP. Since you do not have enough historic data in CFP, you convert your historic data from FP to CFP. Now you can build and use a CFP-based effort estimation model.

The latter two options require that you are able to convert CFP into FP or vice versa.

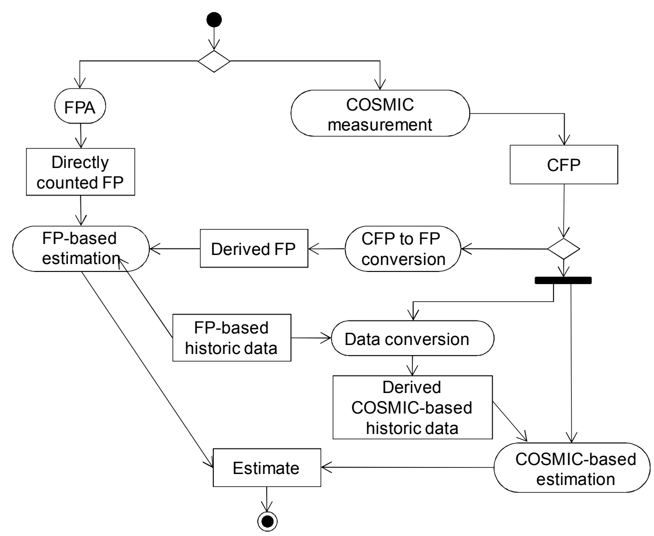

Figure 7. Estimation processes.

As a final remark, it is interesting to point out that the cost and duration of effort estimation are mainly due to size measurement. In fact, the other required activities (such as characterizing the development process and product, or tuning the model) are usually simpler, and likely to become routine activities.

2.4 Conversions of Functional Size Measures

Traditional approaches to the conversion of size measures between CFP and FP are discussed in [12]. In particular, two practically viable procedures are described in [12]:

- The 'manual' conversion of FP to COSMIC. It requires that data concerning FPA BFC are available, and that enough knowledge and expertise are available for converting FPA BFC into COSMIC BFC. In practice FPA data are 'reused' in a COSMIC measurement process. Note that the inverse conversion is not possible, since COSMIC BFC data do not contain enough information to support FPA.
- The statistically-based conversion. It involves finding a reliable correlation between FP size data and CFP size data.

This procedure is the one most commonly adopted (see for instance [4], [13], [14] and [10]).

In both cases, using the conversion in the context of an effort estimation process (Figure 7) requires that the execution of the FPA and/or COSMIC measurement process (as described in Figure 3 and Figure 6) is performed from start to end. Since these processes can be long and expensive, as discussed in Sections 2.1 and 2.2, the conversion contributes in a relevant way to the duration and cost of the effort estimation process.

2.5 Simplified Measurement scenarios

As mentioned in the introduction, this paper aims at exploring the existence of correlations not just between FP and CFP, but also among their base functional components. Finding such correlations implies two types of benefits:

– From a conceptual point of view, it could be possible to understand better the commonalities and differences between the two measurement methods.

– From a practical point of view, it could be possible to find simpler and faster processes to measure FP and/or CFP, thus achieving faster and cheaper effort estimations.

Suppose for instance that for a class of applications it is found that the size in CFP is proportional to the number of functional processes, i.e., that for all applications the average number of data movements per functional process is equal (with a good approximation) to a constant K. Then, the CFP measurement process could be simplified as shown in Figure 8. It is quite evident that this new process would be much faster and cheaper than the whole COSMIC measurement procedure carried out as specified in the manual [3] and illustrated in Figure 6.

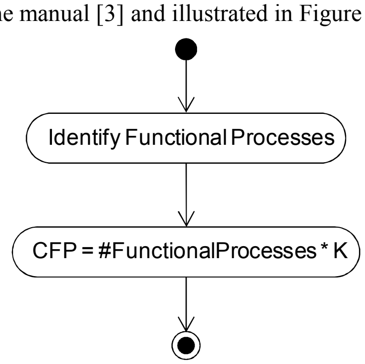

Figure 8. A possible simplification of the COSMIC measurement process.

The same principle applies to Function Point measurement. For instance, if we were able to establish that, for a given class of applications, a correlation between FP on one side and the number of transaction and data functions on the other holds, then we could count FP as described in Figure 9.

The measurement process is Figure 9 is also much faster and cheaper than the traditional process described in Figure 3.

In conclusion we can say that investigating the correlation between functional size metrics and their BFC has relevant practical implications, since it can lead to a simplification (maybe applicable only in particular circumstances) of the functional size measurement procedures.

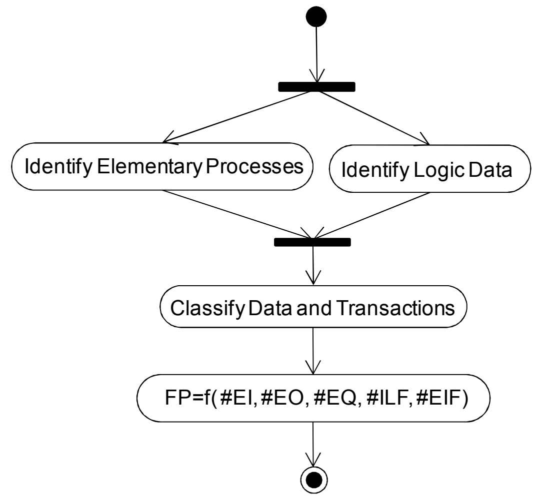

Figure 9. A possible simplification of the FP measurement process.

The possible simplifications sketched above could be even more effective when used in conjunction with model-based measurement techniques, which make identifying and counting some BFC a quite straightforward matter [17], or with measurement techniques that start from rigorous requirements models [18][18].

3. Choice of the dataset and quality assurance

The quality of the data set is fundamental in the type of study reported here. Therefore, the next subsections illustrate the choice of the data set and the data quality assurance activities performed.

3.1 The data set

The work described here is based on the analysis of the data published in [4] by van Heeringen. This data set was chosen because of the following reasons:

– It reports not only the number of CFP and NESMA FP, but also several CFP.

– Having been used by van Heeringen for a traditional study [4] it is suitable to support the comparison of the traditional approach with an analysis involving BFC.

– It is the most numerous of the published data sets correlating FP and CFP.

The considered data are the result of a measuring activity performed by Sogeti in 2006 [4]. They sized 26 projects using both the NESMA and COSMIC methods. In the COSMIC measurements, only the end user measurement viewpoint has been used, to make CFP comparable with FP. The measurements were carried out by experienced counters; hence the quality of the measurement is fairly high. However, the counting was performed on the basis of documentation about requirements that was not always of suitably high quality, being too abstract and incomplete. The projects involved are homogeneous with respect to the application domain, which involved banking, insurance and government organizations.

The data set is reported in Table 1. For each project, the following data are known:

– The functional size in NESMA FP, together with FPA non-weighted base functional components: the number of Internal Logic Files (ILF), External Interface Files (EIF), External Input (EI), External Output (EO), External Queries (EQ).

– The functional size in CFP, together with the number of functional processes. Unfortunately, the number of data movements (the most important BFC of the COSMIC method) was not given in [4].

Table 1. Dataset Sogeti analysis 2006

Proj ID	FP	ILF	EIF	EI	EO	EQ	CFP	Func. Proc.
1	302	11	6	16	19	9	313	54
2	653	13	1	53	53	20	603	110
3	606	17	0	45	55	8	778	152
4	245	6	6	31	23	3	257	43
5	112	2	9	6	4	0	75	8
6	499	16	3	45	34	1	445	66
7	565	34	0	38	25	1	488	64
8	249	14	3	323	14	1	270	36
9	129	1	12	4	6	4	73	14
10	381	0	30	0	42	0	281	42
11	924	45	2	136	7	5	1144	143
12	1076	45	2	136	7	43	1448	181
13	412	14	1	19	21	11	509	51
14	279	11	4	20	20	1	286	44
15	279	11	4	20	20	1	352	44
16	136	3	0	13	11	2	137	25
17	135	3	2	0	0	0	120	15
18	874	32	0	95	39	13	925	159
19	61	1	4	1	6	0	66	7
20	1622	27	4	124	169	1	1864	223
21	627	23	1	58	25	22	714	113
22	586	31	0	75	30	2	620	118
23	741	34	0	49	51	13	893	113
24	498	21	0	63	39	6	530	104
25	286	12	1	20	23	4	252	35
26	334	6	8	26	27	3	301	34

3.2 Project data reliability

In order to guarantee the reliability of the analysis, it is necessary as a first step to evaluate the quality of the data points. The set of available data is therefore analyzed, in order to detect the projects that are characterized by incoherent or contradictory data.

The examination of Table 1 suggests that project 17 should not be considered. In fact, it features 3 ILF, 2 EIF and no transaction function. This is not a feasible situation: on the one hand, a program that does not perform any function does not make sense; on the other hand a program with no transaction could not maintain any ILF, according to FPA rules. Moreover, the FP measure does not match the BFC: with 3 ILF and 2 EIF a system could be at most 55 FP, instead it is reported to be 135 FP. Even considering that NESMA takes into consideration the code tables does not make the reported size feasible. Finally, the lack of transaction functions is not coherent with the fact that 15 COSMIC functional processes were identified for the project. Hence, we drop project 17 from the dataset.

In the rest of the paper, the different types of analysis are performed on the set of data reported in Table 1, except for project 17.

4. The analysis

It would be ideal if sizes measured with traditional methods could be exactly converted to COSMIC sizes by widely-applicable mathematical formulae, but there are theoretical reasons why this is not possible: the BFC of FPA do not map exactly to the BFC's of the COSMIC method and the measurement rules are different [11].

The statistical correlation studies published so far have shown reasonable correlations in various circumstances [4][13][14][10] (see Section 6). Therefore, also considering that statistically-derived convertibility formulae could be easily applicable by organizations wishing to convert their base of FPA measures to COSMIC sizes, the work reported here looks for statistically-based conversion formulae, using regression analysis.

4.1 Correlation of CFP with FP

The correlation of CFP with NESMA FP was analyzed by van Heeringen in [4].

Excluding project 17, the correlation found, represented in Figure 10, is not appreciably different from the one reported in [4]:

CFP = 1.23 FP - 74

$R^2 = 0.97$; the F observed value is 646 >> the 99% probability ($\nu1 = 2$, $\nu2 = 22$) ≅ 6.

The average absolute error is 13.7%, the estimation error being ≥ 20% for 6 projects (i.e., for one fourth of the projects).

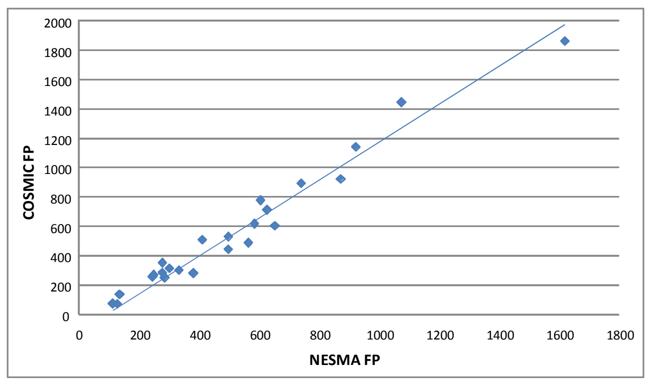

Figure 10. The correlation of COSMIC and NESMA FP.

As in [4], we can observe that the correlation does not work for too small projects. In particular project 19 –which is only 61 FP, about half the size (in NESMA FP) of the second smallest project in the dataset– is underestimated by 88%. Accordingly, the correlation described above excludes project 19.

However, in the following analyses project 19 is often included, since it is interesting to evaluate to what extent the small size of project 19 is tolerated by the various correlations.

4.2 Correlation of CFP with FP base functional components

While in [4] van Heeringen analyzed the correlation between NESMA FP and COSMIC FP, he did not explore the existence of correlations between CFP and the Base Functional Components (BFC) of function points, or between NESMA FP and the COSMIC BFC. Studying these correlations can lead to a deeper understanding of the mutual dependencies of CFP and FP.

In this section we examine the correlation between COSMIC FP and the BFC of NESMA FP, namely the number of not weighted data functions and transaction functions. This correlation is interesting because it relates the CFP to measures (the non-weighted CFP) that are fairly simple to obtain.

The correlation found is:

CFP = 5.75 TF + 7.56 DF – 93

Where TF indicates the not weighted Transaction Functions (i.e., EI+EO+EQ), and DF indicates the not weighted logic files (i.e., EIF+ILF).

$R^2 = 0.96$; the F observed value is 250 >> the 99% probability ($\nu1 = 3$, $\nu2 = 21$) ≅ 5.

The average absolute error is 17.1%, the estimation error being greater than 20% for one third of the projects.

This correlation excludes project 19, which cannot be estimated correctly.

The analysis described above shows that not considering function weights does not affect much the estimation of COSMIC FP. If you do not know the exact number of NESMA FP, but only the number of Data functions and Transaction functions, you can still estimate the CFP with a good precision (very close to the one that can be achieved when data and transaction functions have been properly weighted). You do not even need to classify the transaction functions as input, outputs or queries, which is sometimes a tricky issue.

For new projects, a person used to count FP could easily and quickly get an estimation of CFP without undergoing either the complete FP counting process, or the complete COSMIC measurement process. In fact, just identifying the data and the transaction processes (without even classifying them) allows the measurer to compute a reasonably good estimate of CFP. This is quite interesting in the early phases of development, when the details needed for evaluating the complexity of functions, or for identifying all the data movements, are not known precisely.

Having explored the correlation of CFP with FPA transaction and data functions, we consider now the possibility that a correlation between CFP and transaction functions alone could exist.

The correlation found (Figure 11) is:

CFP = 6.62 TF - 1

$R^2 = 0.94$; the F observed value is 330 >> the 99% probability ($\nu1 = 2$, $\nu2 = 22$) ≅ 6.

The average absolute error = 17.5%, with the estimation error being > 20% for 9 projects.

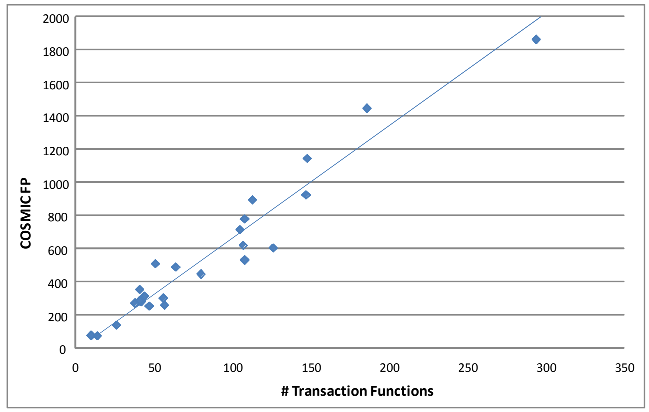

Figure 11. The correlation between CFP and transaction functions.

This correlation excludes project 19; however, including project 19 does not change sensibly the result (both R^2 and the average absolute error do not change appreciably).

This result shows that the knowledge of the data functions is not decisive to estimate CFP. This is an expected result, since the measure of CFP does not depend on the amount of data that is managed by the application being measured.

It is now interesting to understand whether the CFP can be estimated better on the basis of fine granularity knowledge of FPA BFC (i.e., non weighted ILF, EIF, EI, EO, EQ).

In this case the constant term was forced to zero, on the basis of the consideration that providing all FPA BFC should account for the differences in the measurement rules. The correlation found is:

CFP = 5.29 ILF + 0.97 EIF + 5.42 EI + 5.44 EO + 7.75 EQ

$R^2 = 0.98$; the F observed value is 240 >> the 99% probability ($\nu1 = 5$, $\nu2 = 19$) ≅ 4.

The average absolute error = 15.5%, with the error being > 20% for 7 projects out of 25.

This correlation excludes project 19; including project 19 does not change sensibly the result (R^2 remains unchanged, while the average absolute error increases by 0.5 %).

This result shows that considering the BFC separately improves – though marginally– the correlation that involves CFP on one side and the transaction and data functions on the other side.

4.3 Correlation of FP with non-weighted FP base functional components

The fact that CFP can be estimated in a reasonably precise way on the basis of the number of data and transaction functions suggests that we should evaluate whether also FP can be estimated on the basis of such (non weighted!) BFC.

The correlation between the not weighted functions and the FP seems to exist, and it is very good (R^2>0.99).

FP = 5.15 TF + 4.74 DF

where TF = EI+EO+EQ and DF= EIF+ILF.

In this case it is interesting to notice that the correlation was obtained forcing the constant component to be null, consistent with the definition of FP (if DF=TF=0, then FP=0).

The F observed value is 1891 >> the 99% probability ($\nu 1 = 2$, $\nu 2 = 23$) ≅ 6.

The average absolute error is also very low (7.1%), with only three projects featuring an estimation error > 20%.

In this case we do not even need to exclude project 19; actually, it is estimated very well, as are the other small projects.

According to these findings, it appears that the functional size in NESMA FP of projects that are homogeneous to the sample can be estimated easily, quickly and with very good precision without performing the whole measurement process, i.e., without weighing the function types.

4.4 Correlation between FP and transaction functions

Having seen that FP can be estimated on the base of data and transaction functions, it seems useful to check whether also FP can be estimated on the basis of transaction functions alone.

Actually, a very good correlation was found also in this case ($R^2 > 0.96$):

FP = 5.34 TF + 60

The F observed value is 572 >> the 99% probability ($\nu 1 = 2$, $\nu 2 = 22$) ≅ 6.

The average absolute error is 11.7%, with estimation error > 20% for 5 projects.

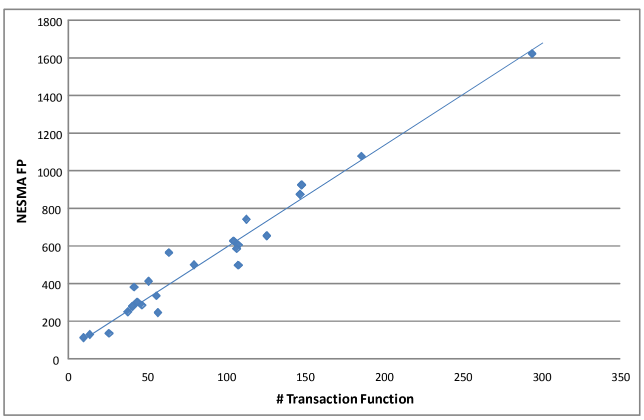

Figure 12. The correlation between the number of transaction function and NESMA FP.

The correlation (Figure 12) was obtained allowing a constant term that somehow represents the contribution of the data functions and excluding project 19 (too small). Including project 19 causes the precision to decrease, but not dramatically (the average absolute error becomes 13.2%).

4.5 Correlation of FP with elementary non-weighted FP BFC

The very good correlation found between FP on one side and data and transaction functions on the other side suggests that we should consider analyzing also the possible correlation between FP and the BFC, namely ILF, EIF, EI, EO and EQ.

Actually, the number of NESMA FP is very well correlated ($R^2>0.99$) to the elementary non weighted BFC. The correlation is:

FP = 7.29 ILF + 4.86 EIF + 3.54 EI + 5.42 EO + 4.84 EQ

The F observed value is 901 >> the 99% probability ($\nu 1 = 5$, $\nu 2 = 20$) ≅ 4.1.

The average absolute error is 6.5%, thus very low, and only in two cases the error is > 20%, the maximum error being around 31%.

As expected, the estimation of FP from the BFCs provides better and more precise results than estimating out of aggregated data (namely, data functions and transaction functions).

The result found is that –at least for a set of homogeneous projects– one can compute an excellent approximation of the size in FP without the burden of evaluating the ‘complexity’ of the function types. This is a relevant benefit, since evaluating the complexity of data and transaction functions is the most cumbersome and time consuming activity of the whole FP counting process. It is also worthwhile noticing that the average absolute error (6.5 %) is less than the reported variability of the counting performed by different certified experts for the same application (it may be up to 10% according to data from the IFPUG [8]).

In the formula of the correlation each coefficient indicates the typical weight of the associated function type. We can thus check whether these values are consistent with the FP computation procedures. The weights of the function types according to the correlation function are reported in Table 2, together with the low, average and high complexity weights specified by FPA.

Table 2. FPA weights and weights found

Function type	FPA Low	FPA Mid	FPA High	Coefficient found
ILF	7	10	15	7.29
EIF	5	7	10	4.86
EI	3	4	6	3.54
EO	4	5	7	5.42
EQ	3	4	6	4.84

It is easy to see that the observed weights of the data functions are very close to the minimum value specified by FPA. Actually, the weight of EIF is slightly less than the FPA minimum, but of a very small amount. The average weight of EI is midway between the minimum and medium, while the average weight of EO and EQ is greater than the medium value.

These data provide a characterization of the set of projects of the sample: they deal with simple data, support simple or average complexity inputs and perform slightly more complex than average outputs and queries. Considering the nature of the sample projects (all “business” applications), this identikit is quite reasonable.

In summary, we can conclude that the correlation found seems perfectly coherent with both the nature of the projects belonging to the sample and the FPA counting rules.

4.6 Correlation between COSMIC functional processes and FP transaction functions

Since we are studying the correlation between CFP and FP, which are both aggregated values (the former being the sum of the data movements, the latter being the weighted sum of function types), it is interesting to investigate whether we can understand why the correlation holds. To this end, we can move to a finer level of granularity, and look for correlations between the BFC of both

CFP and FPA. A good starting point is given by COSMIC functional processes and FP transaction functions, since they represent practically the same concept (*"functional processes in COSMIC will be transactional functions in IFPUG and vice versa"*, according to Cuadrado-Gallego et al. [9]).

Actually, the data set does not include other fine granularity data (like data movements or FTR, DET, etc.), therefore no other investigation concerning fine granularity data is possible. Hence, this section reports the study of the correlation between the COSMIC Functional Processes and the FPA transaction processes, i.e., EI+EO+EQ. Since COSMIC functional processes and FPA transaction processes are defined in very similar ways, we expect that there is a correlation, and that is very close to an identity (i.e., CFP ≅ FPA transactions). In fact, a very good correlation (R^2=0.97) was found:

COSMIC functional processes = 0.93 FPA transaction processes.

The F observed value is 759 >> the 99% probability (ν1 = 1, ν2 = 24) ≅ 8. The average absolute error is 14.2%, the error being > 20% for 6 projects.

Note that in this correlation project 19 was included in the sample set, since there were no reasons to exclude it.

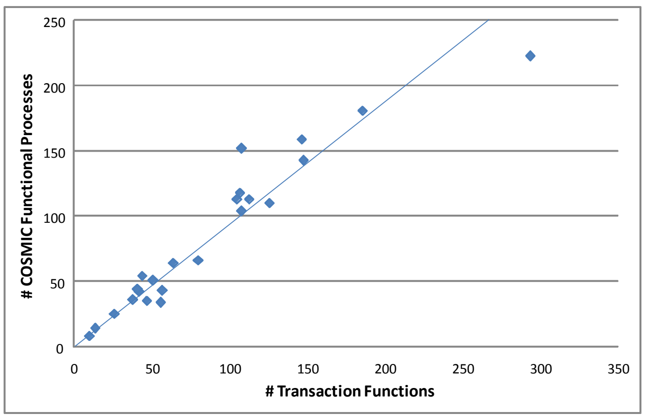

Figure 13. The correlation between COSMIC functional processes and FPA transaction functions.

The correlation found (depicted in Figure 13) confirms the expectations, i.e., that COSMIC functional processes and FP transactions are very similar concepts. It is not clear why the proportion is smaller than 1 (when you move from FP to COSMIC you lose 7% of the processes).

It is also surprising that the average absolute error is relatively high; in 6 cases out of 25 the error is greater than 20%. This datum reflects the fact that in several cases the counters considered the number of COSMIC functional processes to be sensibly different from the FP transaction processes.

Unfortunately, we do not have the elements to explain these strange phenomena. In conclusion we have that on the one hand the expected similarity of the two concepts emerged clearly; on the other hand there are differences that are rather hard to explain.

4.7 Correlation between CFP and COSMIC functional processes

Another interesting analysis is the study of the correlation between the Functional Processes (COSMIC) and the CFP.

The correlation found (Figure 14) is very good (R^2=0.96).

COSMIC FP = 6.97 COSMIC functional processes.

The F observed value is 652 >> the 99% probability (ν1 = 1, ν2 = 24) ≅ 8.

This result shows that homogeneous projects tend to associate an almost constant number of data movements to each functional process. Accordingly, in an early evaluation concerning projects that are similar to those in the Sogeti set one can skip counting data movements and just set the number of COSMIC function points equal to 7 times the number of functional processes. This approximate computation is coherent with the suggestions from the COSMIC measurement manual [12]: the correlation analysis provides the locally-calibrated 'scaling factor' (in this case, 7 data movements per functional process) to convert the number of functional process into CFP.

The average absolute error you get this way is 18.6% (with estimation error > 20% for 10 projects): for an early evaluation this error extent is generally acceptable.

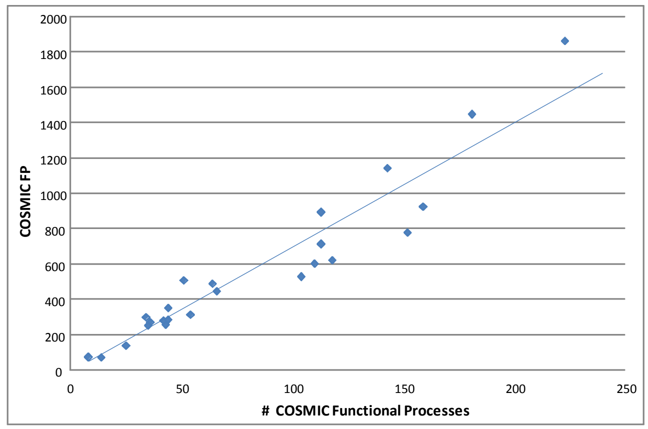

Figure 14. The correlation between COSMIC functional processes and COSMIC FP.

4.8 Correlation between FP and COSMIC functional processes

The correlation reported in this section is of relevant practical value. Suppose that you are measuring the functional size of an application in CFP, and you just finished identifying the functional process, and you need to perform an early cost estimation: if the correlation holds, than you can estimate the size in FP on the base of the number of functional processes (FuncProc), and use the result as an input to a FP-based cost estimation model.

Actually, a very good correlation (Figure 15) was found also in this case, (R^2 > 0.89):

FP = 5.7 FuncProc + 48

The F observed value is 180 >> the 99% probability (ν1 = 2, ν2 = 22) ≅ 6. The average absolute error is 12.5%, with estimation error > 20% for 5 projects.

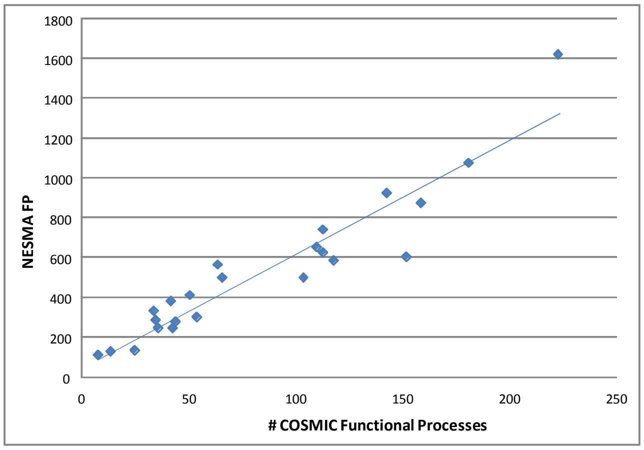

Figure 15. The correlation between COSMIC functional processes and NESMA FP.

The correlation was obtained allowing a constant term that somehow represents the contribution of the data functions and excluding project 19. Including project 19 causes the precision to decrease slightly: the average absolute error becomes 13.6%.

5. Generality of the reported results

Can we apply the reported results to projects that are different from those in the Sogeti dataset? In order to answer this question, some of the correlations reported above have been compared with the data from the literature. Unfortunately it was not possible to check all the correlations studied in the paper, because the literature does not deal with all the issues addressed by this paper.

5.1 Generality of the correlation between CFP and function points

Several papers compare the correlations between traditional FP and COSMIC FP that have been published (see Section 6).

In general, it appears that a strong correlation has been found for all the examined data sets; however, the derived formulas are different, sometimes significantly. Accordingly, the manual suggests that *"an organization wishing to convert using a statistical approach would be best advised to establish its own conversion formula based on data from its own software"* [12]; in summary, the validity of the correlations is strictly local.

5.2 Generality of the correlation between FP and FPA BFC

The datasets reported in [4] and [9] are characterized by similar correlations between FP and FPA BFC, both featuring a very high R^2 and a very small average absolute error (7.1% and 7.6% respectively). Nevertheless, the equations of the correlations are different. From the Sogeti dataset we get:

FP = 5.15 TF + 4.74 DF

From the dataset reported in [9] we get:

FP = 3.76 TF + 7.6 DF

This means that in the Sogeti dataset the transaction functions were more complex, and contributed more FP than the data functions. On the contrary, in the second dataset the data functions provided the greatest contribution.

We can therefore conclude that the notion that FP and FPA BFC are usually correlated, but in ways that depend quantitatively on the specific set of data, is confirmed by the Sogeti dataset.

5.3 Generality of the correlation between CFP and FPA transaction functions

Abran et al. reported in [10] the following correlation between CFP and function points due to transaction functions (TFP):

CFP = 1.35 TFP + 5.5 (R^2 = 0.98).

The same correlation, computed on the data set reported in [11] is: CFP = 1.36 TFP (R^2 = 0.98).

With the Sogeti dataset the correlation is CFP = 6.6 TF + 1, with R^2 = 0.94 (the correlation reported in Section 4.2 is a bit different, since it is obtained forcing the constant to zero).

The latter formula looks different from the former two in the proportionality coefficient (6.58 vs. 1.35 and 1.36), while the constant values are all very small. The reason is that in the former formula transaction functions are weighted, i.e. they represent the function points due to transactions, while in the latter formula the transaction functions (TF) are not weighted.

In order to take into account this important difference, we can reason (in a rather approximate way) as follows: we infer the weight of transaction functions, and use it to evaluate whether the function that relates CFP to TFP for the Sogeti data set is compatible with the correlations reported in [10] and [11].

By computing the correlation between FP and transaction and data functions, we get:

FP = 4.74 FT + 5.15 DF (R^2 > 0.99)

Therefore we can assume that the average weight of transaction functions in the Sogeti sample is 4.74. Dividing 6.6 by 4.74 we get 1.39, a value that is very close to the coefficients reported in [10] (1.35) and [11] (1.36).

In conclusion we can state that the correlation between CFP and transaction functions is valid for the data sets reported in [4], [10] and [11], and is probably valid in general, although the coefficients that determine quantitatively the relation between the two dimensions vary moderately depending on the data set.

6. Related work

As already mentioned, several studies investigated the quantitative relation between traditional function points (e.g., IFPUG or NESMA FP) and CFP, using statistical regression methods. Table 3 lists the results of such studies [12]. Apart from the last dataset of van Heeringen, all the measurements were made on data collected almost entirely within a single organization.

It appears that a strong correlation has been found for all the examined data sets; however, the derived formulas are different, sometimes significantly. Moreover, a considerable part of the projects (20-30%) does not fit well in the regression curve.

The correlations appear correct with respect to the definition of traditional FP and CFP: for instance, the slope ≥ 1 seems to account for the fact that IFPUG elementary processes have a maximum size, while the size of COSMIC functional processes is limited only by the number of data groups involved in the process.

Some authors have noticed that the proposed correlation does not work well for small projects. Hence, different correlations for projects smaller than 200 FP have been studied. These investigations reported that the true ‘average relationship’ between the IFPUG and COSMIC size scales should start with a slope significantly less than 1 (circa 0.68) and become steeper (around 1.24) above about 200 FP.

Cuadrado et al. have published a method based on a mapping of the IFPUG and COSMIC BFC that gives an empirically-defined upper and lower bound for the COSMIC size corresponding to a given IFPUG size [9]. The method requires knowledge of the number of file type references made in each of the elementary processes of the IFPUG measurement. The merit of that work is mainly in the exploration of the nature of the relations that link FPA and COSMIC BFC. However, according to the reported results, the method is of little practical value: on the one hand, it is expensive, since you have to perform most of the FP measurement process (as you need to identify FTR); on the other hand, you only get a relative wide range of possible values for the size in CFP (on average, the estimate is in the -29..+26% range).

7. Conclusions

Section 4 showed that several interesting correlations exist among the two considered types of functional size measurements and their BFC. These results are summarized in Table 4 (where AAE indicates the average absolute error).

All the correlations found are characterized by quite high values of R^2 and provide reasonably precise models for estimating the functional size (either in FP or in CFP).

Table 3. Summary of the correlations found by previous studies

Author	# data points	Size Range (FP)	Conversion Formula obtained by regression analysis	R^2
Fetke (1999) [13]	4	40 – 77	CFP = 1.1 x FP (IFPUG) – 7.6	0.97
Vogelezang & Lesterhuis (2003) [14]	11	39 – 1424	CFP = 1.2 x FP (NESMA) – 87	0.99
Abran, Desharnais, Azziz (2005) [10]	6	103 – 1146	CFP = 0.84 x FP (IFPUG) + 18	0.91
Desharnais, Abran, Cuadrado (2007) [11]	14	111 – 647	CFP = 1.0 x FP (IFPUG) – 3	0.93
Van Heeringen (2007) [4]	26	61 – 1422	CFP = 1.22 x FP (NESMA) – 64	0.97

Table 4. Summary of the correlations found

	FP	#ILF,EIF, EI,EO,EQ	#TF (EI+EO+EQ)	#TF(EI+EO+EQ), DF (EIF+ILF)	COSMIC Func. Processes
FP		$R^2 > 0.99$ AAE = 6.8%	$R^2 = 0.96$ AAE = 12%	$R^2 > 0.99$ AAE = 6.5%	$R^2 = 0.89$ AAE = 12%
CFP	$R^2 = 0.97$ AAE = 14%	$R^2 = 0.98$ AAE = 15%	$R^2 = 0.94$ AAE = 17%	$R^2 = 0.96$ AAE = 17%	$R^2 = 0.96$ AAE = 19%
COSMIC Func. Procecces			$R^2 = 0.93$ AAE = 14%		

In particular, the results found tend to suggest that in presence of a set of projects that are quite homogeneous –with respect to the application domain, the nature of computation performed, and the implementation technology– it is possible to obtain fairly precise estimations of the functional size (expressed either in FP or in CFP) on the basis of a few BFC. Such results can be useful when performing early or quick estimations, i.e., before the requirements have been specified down to the level of detail where the precise size measurement is possible, or when a measurement is needed but there is insufficient time to measure the required size using the standard method.

From the methodological point of view the variety of strong observed correlations indicates that it is necessary to investigate whether this is a ‘lucky’ data set or the observed properties are typical of every set of reasonably homogeneous projects. To this end, every study of the correlation of traditional and COSMIC FP should be complemented with the evaluation of the correlations illustrated in Section 4.

From a practical point of view, we can conclude that –at least in restricted environments, such as the one that produced the considered data set– the functional size (either in CFP or in function points) can be assessed without applying to the full extent the measuring procedures suggested by COSMIC or NESMA (or IFPUG, FISMA, etc.).

Actually, the simplifications of the COSMIC and FPA measurement processes anticipated in Section 2.5 seem viable. In fact, Table 4 shows that we can get an excellent approximation of the size in FP on the basis of not weighted FPA base functional components (EIF, ILF, EI, EO, EQ), getting an estimate that –on average– features an error that is less than the typical variability of the measurement due to different measurers. In this way (see Figure 9) you skip the expensive phases of function analysis and weighing.

Also CFP can be estimated on the basis of not weighted FPA BFC or functional processes, thus saving the most expensive phases of the measurement process. In particular, it is interesting to note that converting FP into CFP provides a little advantage (a 2% increase in precision) with respect to estimating CFP on the basis of FPA BFC (not weighted ILF, EIF, EI, EO and EQ). As a side observation, it is interesting to note that in order to estimate CFP on the basis of FP you need to exclude project 19 from the data set that generates the conversion formula; on the contrary, when correlating CFP to FPA BFC, there is no need to exclude project 19. This means that in the computation of function points you lose information with respect to the set of BFC. This is yet another piece of evidence that using a single number that takes into account different aspects (data and functions) of the application is not a good idea: using an array of values provides more detailed information.

In conclusion, finding a law that relates CFP to FP does not appear to be strictly necessary, at least as long as you consider a set of applications having similar characteristics.

Of course, it would be interesting to know if the correlations reported in this paper are of general validity, because such result would imply that the simplified counting processes suggested by the correlations can be universally applied. Future work includes the replication of the types of analysis reported here with other data sets, in order to assess the generality of the results reported in this paper.

Moreover, since functional size measurement is mainly required for effort estimation, it would be interesting to evaluate the performance of the conversion methods described above when used within an actual effort estimation process. Unfortunately it was not possible to get effort data concerning the Sogeti data set, since they are confidential. Future work includes experimentations not only with size estimation, but also with effort estimation.

Acknowlegments
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8. REFERENCES

[1] Albrecht, A.J. 1979. Measuring Application Development Productivity, *Joint SHARE/ GUIDE/IBM Application Development Symposium*.

[2] International Function Point Users Group 2004. *Function Point Counting Practices Manual - Release 4.2*.

[3] COSMIC – Common Software Measurement International Consortium 2007. *The COSMIC Functional Size Measurement Method - version 3.0 Measurement Manual (The COSMIC Implementation Guide for ISO/IEC 19761: 2003)*, September 2007.

[4] van Heeringen, H. 2007. "Changing from FPA to COSMIC - A transition framework", *Software Measurement European Forum 2007* (Rome, May 9-11, 2007).

[5] ISO/IEC 24750: 2005, *Software engineering – NESMA functional size measurement method version 2.1 – Definitions and counting guidelines for the application of Function Points Analysis*, International Organization for Standardization -- ISO, Geneva, 2005

[6] ISO/IEC 20926: 2003, *Software engineering – IFPUG 4.1 Unadjusted functional size measurement method – Counting Practices Manual*, ISO, Geneva, 2003.

[7] NESMA 2004. *Definitions and counting guidelines for the application of function point analysis – NESMA Functional Size Measurement method compliant to ISO/IEC 24570 version 2.1*, Netherlands Software Measurement user Association.

[8] Buglione, L. 2008. *Misurare il software*. Franco Angeli (in Italian).

[9] Cuadrado-Gallego, J.J., Rodriguez, D., Machado, F., and Abran, A., 2007. "Convertibility between IFPUG and COSMIC Functional Size Measurements", *8th Int. Conference on Product-focussed Software Process Improvement*, (Riga, Latvia, July 2007).

[10] Abran, A., Desharnais, J.-M., and Azziz, F., 2005. "Measurement Convertibility: From Function Points to COSMIC," *15th International Workshop on Software Measurement – IWSM 2005*, (Montréal, Canada, Sept. 12-14, 2005), Shaker Verlag.

[11] Desharnais, J-M., Abran, A. and Cuadrado, J., 2006. "Convertibility of Function Points to COSMIC: Identification and analysis of functional outliers", *Int. Conference on Software Process and Product Measurement – MENSURA 2006*, (Madrid 2006).

[12] COSMIC – Common Software Measurement International Consortium, 2007. *The COSMIC Functional Size Measurement Method Version 3.0 - Advanced and Related Topics*, December 2007.

[13] Fetcke, T., *The warehouse software portfolio, a case study in functional size measurement*, Technical report no. 1999-20, Département d'informatique, Université du Quebec à Montréal, Canada, 1999

[14] Vogelezang, F.W., and Lesterhuis, A., 2003. Applicability of COSMIC Full Function Points in an administrative environment: Experiences of an early adopter, *13th International Workshop on Software Measurement – IWSM 2003*, (Montréal, 2003) Shaker Verlag.

[15] Cuadrado-Gallego, J.J., Buglione, L., Rejas-Muslera, R.J., and Machado-Píriz, F., 2008. "IFPUG-COSMIC Statistical Conversion", *34th Euromicro Conference Software Engineering and Advanced Applications*, (Parma, Italy September 3-5, 2008).

[16] Boehm, B. W., Horowitz, E., Madachy, R., Reifer, D., Clark, B., Steece, B., Winsor Brown, A., Chulani, S., Abts, C., 2008. *Software Cost Estimation with Cocomo II*, Prentice Hall.

[17] Lavazza, L., del Bianco, V. and Garavaglia, C. 2008. "Model-based Functional Size Measurement", *ESEM 2008, 2nd International Symposium on Empirical Software Engineering and Measurement*, (Kaiserslautern, October 9-10, 2008).

[18] Lavazza, L. and Del Bianco, V. 2008. "Functional Size Measurement based on Problem Frames: a Case Study", 3rd International Workshop on Advances and Applications of Problem Frames (IWAAPF), (Leipzig, May 2008).

[19] del Bianco, V. and Lavazza, L. 2009. "Applying the COSMIC Functional Size Measurement to Problem Frames", *14th IEEE International Conference on Engineering of Complex Computer Systems*, (Potsdam, June 2-4 2009).