Software Development Productivity of European Space, Military, and Industrial Applications

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Abstract—The identification, combination, and interaction of the many factors which influence software development productivity makes the measurement, estimation, comparison and tracking of productivity rates very difficult. Through the analysis of a European Space Agency database consisting of 99 software development projects from 37 companies in 8 European countries, this paper seeks to provide significant and useful information about the major factors which influence the productivity of European space, military, and industrial applications, as well as to determine the best metric for measuring the productivity of these projects. Several key findings emerge from the study. The results indicate that some organizations are obtaining significantly higher productivity than others. Some of this variation is due to the differences in the application category and programming language of projects in each company; however, some differences must also be due to the ways in which these companies manage their software development projects. The use of tools and modern programming practices were found to be major controllable factors in productivity improvement. Finally, the lines-of-code productivity metric is shown to be superior to the process productivity metric for projects in our database.

Index Terms—Software productivity; software effort estimation; European software projects; space, military, and industrial software projects; empirical study of software projects.

1 Introduction

Over the last 25 years, the growing cost of software development has increasingly focused the attention of industry, commerce and government on the software development process. In an attempt to control this process, engineering techniques which use metrics, measurements and models to make quantitative assessments of the cost, productivity and quality of software development were first introduced in the late '60s. Although initially the development of software was perceived to be more of an art and thus outside of these engineering approaches, in the last decade there has been a growing realization among researchers and managers of the need for a disciplined approach to software development and a better quantification of software attributes. Many books have been published in recent years on the need for metrics in software development [13], [17], [18], [19], [26], [31], [32], [34]. Consequently, the development and use of metrics which describe both the software itself and the software development process have become more and more widespread.

Productivity rates are highly variable across the software development industry [3]. Some of the many factors that appear to influence software development productivity are: people factors, such as experience and team size; process factors, such as programming language and tools; product factors, such as complexity and software type; and computer factors, such as storage and timing constraints [13]. The combination and interaction of all of these factors makes the measurement, estimation, comparison and tracking of productivity rates very difficult.

Past software development productivity research has taken two main directions: in the first, research has concentrated on determining the factors which have a significant effect on productivity; and in the second, the emphasis has been on determining the best way to measure productivity. As the results of previous research differ and are limited to programming environments which are similar to those studied, it is important to examine additional databases to improve our understanding

In this paper, we present the results of our analysis of the European Space Agency software development database which, at the time of the analysis, consisted of 99 projects from 37 companies in 8 European countries. This database is unique in that we have found no other published research which analyses the factors which have a significant effect on software development productivity of European non-MIS applications. Our research also adds to overall management of software development knowledge in that we have been able to look in detail at the reasons for differences in productivity at the company level.

The objectives of this paper are twofold: first, to provide significant and useful information about the major factors which influence the productivity of European space, military and industrial applications; and second, to compare the results of using different productivity metrics in order

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to determine which metric is better for measuring the productivity of projects similar to those in our dataset. In our analysis, we employ parsimonious models to examine the impact of differences in company, country, category, language, environment, team size, project duration, and system size, as well as the following seven COCOMO factors [8]: required software reliability, execution time constraint, main storage constraint, virtual machine volatility, programming language experience, use of modern programming practices and use of software tools, on lines-of-code productivity, and process productivity [32].

The remainder of this paper is organized as follows. An overview of prior productivity research is presented, followed by a description of the database and our productivity analysis. The results of the productivity analysis are then presented and compared with the findings of other researchers. A summary of the results can be found in the concluding section.

2 Prior Research

Productivity rates are highly variable across the software development industry [3]. Consequently, early research in cost estimation concentrated on determining causes for the wide variation of project productivity. An overview of some of the productivity factors considered by past researchers can be found in Table 1. In an IBM study by Walston and Felix [39], 29 factors that were significantly correlated with productivity were found. In an analysis of data from the NASA/Goddard Space Flight Center, Bailey and Basili [4] identified 21 productivity parameters. At ITT, Vosburgh et al. [38] found 14 significant productivity factors, with modern programming practice usage and development computer size explaining 24% of the variation in productivity. In Boehm's COCOMO model [8], 15 software factors which had a significant impact on productivity were identified. However, such major factors as application type and programming language were omitted in these models.

Several studies attempt to determine nominal productivity rates depending on the type of software [15], [30], [32]. The productivity of subsystems that were part of a ballistic missile defense system were found to be a function of software type, with real-time software having the lowest productivity [35]. Vosburgh et al. [38] identified three different programming environments with business applications having the highest average productivity followed by normal-time and real-time applications. These environments were characterized by the hardware used, resource constraints, application complexity and programming language. However, the difference in programming environment was not identified as one of their 14 significant productivity factors and it is not clear how much variation in productivity was accounted for by this segmentation.

Aron [1] found that the variation of productivity for a group of IBM projects involving systems programs and business applications was due to differences in system difficulty, characterized by the number of interactions with other system elements, and project duration. He also adjusted his cost estimate for the use of higher-level languages. Kitchenham [29] found that productivity varied

TABLE 1
OVERVIEW OF SOME PRODUCTIVITY FACTORS CONSIDERED IN PAST RESEARCH

Some Major Productivity Factors	ESA Data	A*	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Country	X											X							
Company	X														X				
Category/Type	X											X	X		X		X		
Industrial/Business Environment	X												X		X				
Language	X	X	X			X							X	X					
Team Size	X						X			X	X								
Duration	X	X					X									X	X		
Project Size	X		X			X			X		X		X				X	X	
Required Software Reliability	X							X											
Execution Time Constraint	X							X	X									X	X
Main Storage Constraint	X							X	X									X	X
Virtual Machine Volatility	X							X											
Programming Language Experience	X			X				X	X					X					X
Modern Programming Practices	X		X	X	X			X	X	X			X	X	X	X		X	X
Tool Use	X				X			X		X			X	X		X			
Product Complexity				X				X	X					X	X	X		X	X
Analyst Capability					X			X						X		X			
Applications Experience				X	X			X	X					X		X			X
Programmer Capability				X	X			X						X	X				
Virtual Machine Experience				X		X		X	X					X					X
Amount of Documentation							X			X									X
Overall Personnel Experience										X			X	X				X	X
Customer Interface Complexity				X					X					X				X	X
Design Volatility				X					X	X				X		X		X	X
Hardware Concurrent Development									X									X	X
Quality Assurance					X					X						X			
Development Environment (Online)			X			X								X	X				

* *Table 2 describes the research referred to by each letter.*

with programming language level and working environment. Productivity has also been found to vary with hardware constraints [8], [38], programmer experience [8], [26], [30], [37], [38], [39], team size [10], [13], [23], duration [1], [7], project size [2], [6], [13], [23], [24], [32], [38], and modern programming practices [5], [8], [11], [26], [38], among other factors. As many of these findings differ and are limited to programming environments which are similar to those studied, there is a need for additional research on other databases to determine the applicability of past results to similar projects. An overview of the major databases which include productivity factors can be found in Table 2.

A second area of productivity research has concentrated on determining the best way to measure productivity. In software development terms, productivity is conventionally defined as source lines of code (SLOC) per manmonth. It is a measure of the amount of product produced per unit of human effort. We will refer to this measure as lines-of-code productivity.

$$Lines\text{-}of\text{-}code\ Productivity = \frac{SLOC}{Manmonths\ of\ Effort} \quad (1)$$

This relationship has been the basis for many software estimation methods. A new measure of productivity using lines-of-code has recently been developed by Putnam and Myers [32].

$$Process\ Productivity = \frac{SLOC}{\left(\frac{Effort}{B}\right)^{1/3} (Time)^{4/3}} \quad (2)$$

where SLOC is developed, delivered lines of source code, Effort is the manpower applied to the work measured in manmonths or manyears, B is a skills factor which is a function of system size, and Time represents the duration of the work measured in months or years. Putnam and Myers maintain that process productivity is superior to simple lines-of-code productivity because it covers a complex set of factors affecting the entire software development organization throughout the development process. Their process productivity parameter is based on the analysis of a 750-system database which included projects primarily from the United States, but also from England, Australia, and Japan.

Much discussion concerns the validity of using lines-of-code in the measurement of productivity. According to Jones [26] there are three serious deficiencies associated with lines-of-code:

1) The lack of an international standard for a line of code that encompasses all procedural languages.
2) Software can be produced by program generators, spreadsheets, graphic icons, etc. all of which make the effort of producing lines-of-code irrelevant.
3) Lines-of-code metrics paradoxically decrease as the level of the language gets higher, making the most powerful and advanced languages, such as Ada and C, appear less productive than primitive low-level languages, such as Assembler.

In order to avoid the lines-of-code problem, Halstead [20] defined the size of a program by decomposing lines-of-code into a collection of tokens that were classified either as operators, which are separate data portions, or operands, which are separate functional portions. Productivity was then measured as the number of tokens produced per manmonth. However, the Halstead metrics are now known to be based on questionable assumptions and to contain many sources of error [14].

TABLE 2
OVERVIEW OF MAJOR DATABASES WHICH INCLUDE PRODUCTIVITY FACTORS

Database Code in Table 1	Reference	No. Projects	Environment	Geographical Scope	Productivity Measure
ESA Data	Our research	99	Space/Military/Industrial	Europe	L.O.C.
A	Aron 1976	9	IBM Large Systems	USA	L.O.C.
B	Albrecht 1979	22	IBM Data Processing	USA	F.P.
C	Bailey and Basili 1981	18	Space (NASA/Goddard)	USA	L.O.C.
D	Banker et al. 1991	65	Commercial Maintenance Projects	USA	F.P. and L.O.C.
E	Behrens 1983	24	Data Processing	USA	F.P.
F	Belady and Lehman 1979	37	Not Identified	USA	L.O.C.
G	Boehm 1981	63	Mixture	USA	L.O.C.
H	Brooks 1981	51	Mixture (from Walston-Felix)	USA	L.O.C.
I	Card et al. 1987	22	Space (NASA/Goddard)	USA	L.O.C.
J	Conte et al. 1986	187	Mixture	USA	L.O.C.
K	Cusumano and Kemerer 1990	40	Mixture	USA and Japan	L.O.C.
L	Jones 1991	4,000	Mixture (primarily Systems and MIS)	USA	F.P. (converted from L.O.C.)
M	Kitchenham 1992	108	Not Identified (probably Commercial)	Europe (1 company)	F.P.
N	Lawrence 1981	278	Commercial	Australia	L.O.C.
O	Nevalainen and Mäki 1994	120	Commercial	Finland	F.P.
P	Putnam and Myers 1992	1,486	Mixture (primarily Business Systems)	Primarily USA, also Canada, Western Europe, Japan, and Australia	L.O.C.
Q	Vosburgh et al. 1984	44	Mixture (from ITT)	9 countries	L.O.C.
R	Walston and Felix 1977	60	Mixture (from IBM)	USA	L.O.C.

In the late '70s, Albrecht [2] developed a new measure of productivity by replacing the lines-of-code measurement with function points. Function points are based on the functionality of the software as seen by the user. He calculated the total number of function points by weighting the sums of five different factors: inputs, outputs, logical files, inquiries, and interfaces. Since Albrecht's initial work, many other methods of measuring functionality have been developed [16], [21], [36] to name but a few.

The main disadvantage of function point methods is that they have been created and used primarily in business systems environments. The function point method gives misleading counts for software which has a high algorithmic complexity but low numbers of inputs and outputs [26]. This means that function points are not necessarily an accurate measure of functionality for real-time software, defense systems, systems software, embedded software, communications software and process control software.

Another method, feature points, was developed by Software Productivity Research in 1986 [26]. This method applies an expanded function point logic to system software by including the number of algorithms in the application [27]. It has been applied experimentally to embedded software, real-time software, CAD, AI, and MIS software. However, the use of the feature point method is not yet widespread.

Although the lines-of-code metric is the subject of much debate, the fact remains that it is considered by many organizations as a more practical productivity metric than the currently available alternatives [9]. In a recent study by Cusumano and Kemerer [15], the lines-of-code metric was chosen to compare productivity across a number of organizations in the US and Japan. Previous research has also shown that function points and lines-of-code tend to be highly correlated in the case of new software development [5].

Until the use of function and feature point methods become common for non-MIS applications, and particularly in the domain of space, military, and industrial applications, statistical analysis undertaken of large heterogeneous databases will have to rely upon measuring and analyzing the productivity of these types of projects using lines-of-code metrics.

3 THE ESA DATABASE

In 1988, the European Space Agency (ESA), faced with the evaluation of proposals for large space programs and their huge needs for software development, began compiling a software metrics database focusing on cost estimation and productivity measures. Subsequently, the database was expanded to include military and industrial applications. This activity is ongoing, and at the time of this analysis contained a selection of 99 completed projects from 37 companies in eight European countries. The variables contained in the database are described in more detail in Fig. 1a and 1b and Table 3. The projects represent 5.14 million lines of source code (range: 2,000–413,000, average: 51,910, median: 22,000), 18 development languages or combinations of languages, and 28,328 manmonths of effort (range: 7.8–4,361, average: 292, median: 93). The breakdown of projects by application environment was: military 39%, space 28%, industrial 24%, and other 9%.

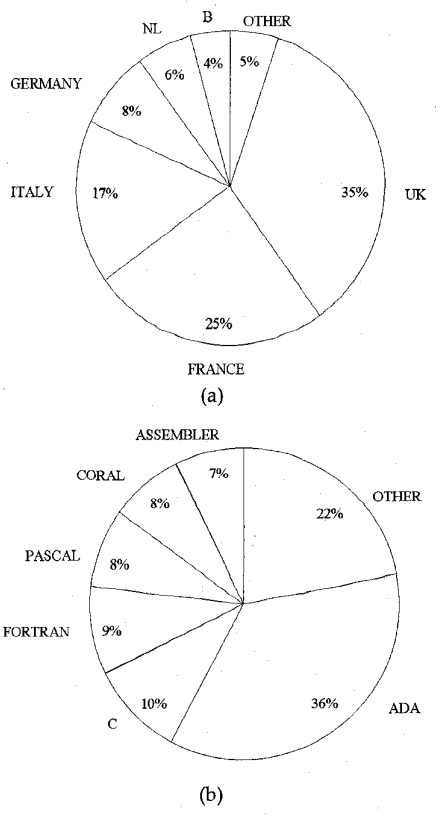


Fig. 1. (a) Main countries represented; (b) main languages represented.

The database collection effort consists of contacting each supplier of data on a regular basis to determine if suitable projects are nearing completion. When a completed questionnaire is received, each supplier of data is telephoned to ensure the validity and comparability of his responses. For example, we verify that the project has actually been completed and that the numbers provided are actuals and not estimates. We also verify that the definitions of SLOC, Effort and COCOMO factors have been understood, that the project is put into the correct category and each company's definition of a manmonth. Other discrepancies, such as the total duration not equaling the duration in calendar months, are also checked. In the ESA database, SLOC and Effort are defined as follows:

SLOC: the amount of nonblank, noncommented delivered lines of code. As the software developed in some projects consists of reused code, adaption adjustment factors [8] were used to correct the size of the software. When no adaptation adjustment factor was available, the new code size was used as a measure for the size.

Effort: The total effort was measured in manmonths and was defined as beginning at specifications delivery and ending at customer acceptance. The effort value covers all directly charged labor on the project for activities during this period. All effort data has been converted to manmonths of 144 manhours per manmonth.

In return, each data supplier receives periodic data analysis reports and diskettes of the sanitized dataset.

TABLE 3
VARIABLES IN ESA DATASET

LANG (18)[1]		Application Programming Language
8 main languages	ADA	Ada
	PAS	Pascal
	FOR	Fortran
	LTR	LTR
	C	C
	TAL	TAL
	COR	Coral
	AS	Assembler
ENV (3)		Environment (Space, Military, Industry)
CATEGORY (8)		ESA Classification
	OB :	On Board
	MSG :	Message Switching
	RT :	Real Time
	GSE :	Ground Support Equipment
	SIM :	Simulators
	GRD :	Ground Control
	TL:	Tool
	OTH :	Other
COUNTRY (8)		Country where project was developed
COMPANY (37)		Company where project was developed
TEAM		Maximum size of implementation team
DUR		Duration of project in months
KLOC		Kilo Lines of Code
Cocomo factors	range	
RELY	1-6	Required Software Reliability
TIME	1-6	Execution Time Constraint
STOR	1-6	Main Storage Constraint
VIRT	1-6	Virtual Machine Volatility
LEXP	1-6	Programming Language Experience
MODP	1-6	Use of Modern Programming Practices
TOOL	1-6	Use of Software Tools

4 DESIGN OF ANALYSIS

Two productivity metrics were used in the analysis of our dataset: lines-of-code productivity and process productivity as defined previously in (1) and (2). Parsimonious models were employed to examine the impact of differences in company, country, category, language, environment, team size, project duration and system size, as well as the following seven COCOMO factors [8]: required software reliability, execution time constraint, main storage constraint, virtual machine volatility, programming language experience, use of modern programming practices and use of software tools, on lines-of-code productivity, and process productivity. As the data was not normally distributed, the measure of correlation used was Spearman's rank correlation coefficient [17]. Any two variables with a correlation coefficient exceeding + or – 0.75 were considered to be highly correlated and were not included in the same model. A General Linear Models procedure [33] which can analyze the variance of unbalanced data was used for this analysis. The variables which explained the greatest amount of the variance of productivity were identified and the dataset was divided into relevant subsets of productivity values. Crossed effects of class variables were taken into consideration. The analysis was performed in an unbiased way: all values were considered as being equally reliable and relationships were extracted based on the face value of the data. Both additive and multiplicative (log) models were fit to the data.

1. The number of categories is in parentheses.

$$\text{Additive: Productivity} = a + b \times x_1 + c \times x_2 + \cdots \quad (3)$$

$$\text{Multiplicative: Productivity} = a \times x_1^b \times x_2^c \times \cdots \quad (4)$$

where a is a constant which varies with the significant class variable(s).[2]

The first phase of the analysis was concerned with determining which individual variables explained the greatest amount of variation of productivity measured as lines-of-code per manmonth. The results of the analysis of all individual class variables are presented in a summary table. As it would not be wise to base our conclusions on the analysis of class levels that contain limited observations, results are shown for the analysis of all of the data as well as for subsets that contain a sufficient number of observations at each class level. The results of these subsets are then examined individually. The results of models based on individual non-class variables are also presented and are used to explain the differences in the class variables.

In the second phase of the analysis, combinations of two class variables were analyzed to find the model which could explain the highest amount of productivity variance. A summary table of results and a matrix of productivity values for the best 2-class variable model are presented. In the third phase of the analysis, the results of models based on combinations of all variables are presented. Finally, the results of comparing lines-of-code productivity with process productivity are presented in the fourth phase of the analysis.

5 PRESENTATION OF RESULTS

5.1 Phase I—Analysis of Variance Models Based on Individual Variables

5.1.1 Summary

In this phase, the variance explained by each variable alone is summarized. This is followed by a detailed discussion of the effect on productivity of each variable. The single variable which explained the greatest amount of variance (55%) of productivity in the dataset was Company. This highlights the need for companies to establish their own software metrics database in addition to benchmarking their data against that of other companies. This was followed by Language (48%) and Category (34%). The Country in which the software was developed explained only 27% of the variation in productivity. The results of analyzing only subsets of class variables where each level contained a sufficient number of projects did not have much effect on the results except for Language. Limiting Language to the eight languages used in four or more projects caused the amount of variance explained by Language to decrease from 48% to 39%. A summary of the analysis can be found in Table 4. Models were also run to determine if maximum team size, the duration of the project or the system size (KLOC) could be used to explain some of the variation in productivity. In addition, analysis was carried out on a subset of the ESA database which included data for seven COCOMO cost drivers [8]: required software reliability, execution time

2. For the 2-class models, a is a function of the crossed effects of two class variables.

TABLE 4
SUMMARY OF ANALYSIS OF INDIVIDUAL CLASS VARIABLES

CLASS VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL[3] (significance)
Company	64	55 %	189	Add (.0001)
Language	97	48 %	.77	Log (.0001)
subset Language	83	39%	.75	Log (.0001)
Category	97	34 %	.82	Log (.0001)
subset Category	92	33%	.81	Log (.0001)
Country	94	27 %	272	Add (.0003)
subset Country	92	25%	272	Add (.0001)
Environment	88	15 %	.91	Log (.0010)

TABLE 5
SUMMARY OF ANALYSIS OF INFLUENCE OF NONCLASS VARIABLES

VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL (significance)
STOR	59	53 %	.81	Log(.0001)
TIME	59	41 %	.72	Log(.0001)
TOOL	60	32 %	.77	Log(.0001)
RELY	93	27 %	.81	Log(.0001)
MODP	59	24 %	.82	Log(.0001)
TEAM	74	19 %	.91	Log (.0001)
DUR	57	12 %	.93	Log (.0088)
KLOC	96	5 %	.93	Log (.0308)
VIRT	59			not significant
LEXP	60			not significant

TABLE 6
MEAN LINES-OF-CODE PRODUCTIVITY BY COMPANY

COMPANY	C2 (3)[4]	C3 (4)	C1 (7)	C5 (7)	C8 (4)	C7 (3)	C6 (3)	C10 (25)	C9 (3)	C4 (5)
MEAN PRODUCTIVITY	853	554	524	479	425	293	268	203	131	84
% LOW PROD. LANGUAGE	0	0	0	0	0	0	0	44	67	0
% LOW PROD. CATEGORY	0	0	0	14	25	0	67	4	100	100

constraint, main storage constraint, virtual machine volatility, programming language experience, use of modern programming practices, and use of software tools. Table 5 shows the amount of variance for each variable individually.

5.2 Phase Ia—Analysis of Variance by Individual Class Variables

5.2.1 Analysis of Variance by Company

The difference in Company alone explained 55% of the variation in productivity. A subset of 64 projects from 10 companies which had supplied data for three or more projects was analyzed. Table 6 lists the average productivity for each company. Some explanations for the difference in productivity across companies are: more projects in a low productivity category; more use of a low productivity language; differences in product, computer, personnel and project attributes; more successful at managing software projects; and differences in quality of end product. The low productivity of four of the five least productive companies was due to the fact that most of their projects were in the low productivity categories of On Board and Message Switching and/or used the low productivity languages Coral and Assembler. However, this explanation does not account for the nearly 300% difference in productivity between company 2 and company 7. Some of this difference must also be due to the ways in which these companies manage their software development projects. In his analysis of 278 commercial programs from 23 companies, Lawrence [30] also found that some organizations obtained significantly higher productivity than others, although no industry pattern was evident. He suggested that the identification of proper organizational variables, such as morale, group norms, personality, management style, level of supervision, training, and employee selection criteria, could contribute to a better understanding of programming productivity variations.

Some further insight into these large productivity differences can be gained from the analysis carried out on a subset of the ESA database which included data for the seven COCOMO cost drivers described previously. The 300% difference in the productivity between company 7 and company 2 can thus be explained by the fact that company 2 projects had lower reliability requirements, and a higher use of tools and modern programming practices (see Fig. 2). The least productive company, company 4, had projects

3. The type of model has an effect on the definition of mean productivity. The mean productivity of an additive model is the average of the productivities. The mean productivity of a log model is the inverse natural log of the mean of the ln of the productivities.

4. Number of projects is shown in parentheses.

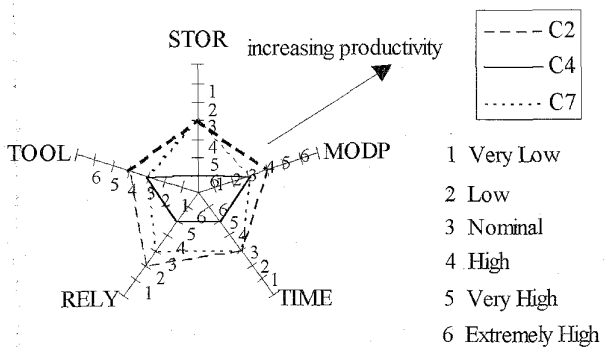
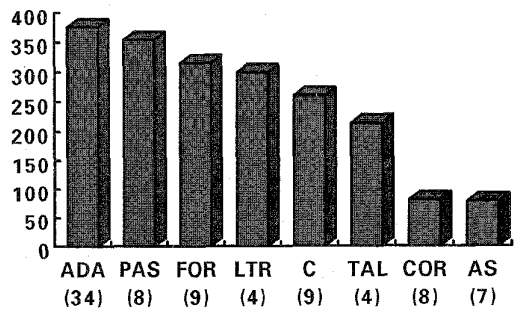


Fig. 2. Median scores of significant productivity factors for companies in ESA dataset.



The number in parentheses is the number of observations.

Fig. 3. Mean lines-of-code productivity by language.

with very high required reliability, execution time constraints and storage constraints. As these three requirements are fixed, this suggests that the use of tools and modern programming practices are major controllable factors in productivity improvement.

5.2.2 Analysis of Variance by Language

A number of researchers have found that productivity, measured using either lines-of-code or function points, varies with the level[5] of the programming language [1], [2], [6], [26], [29]. Some productivity studies have removed this effect either by considering only programs written in the same language [5], [12], [30], or by converting all data into one language using conversion factors [15]. In the ESA dataset, language alone explained 48% of the variation in productivity of 99 projects coded in 18 languages or combinations of languages. A subset of 83 projects coded in languages that had four or more observations was also analyzed in more detail. Fig. 3 shows clearly that Coral and Assembler are low productivity languages.

It is interesting to note that in the ESA dataset the higher level languages, such as Ada, do not appear less productive than the low level Assembler language when measuring productivity in lines-of-code. This result contradicts the lines-of-code paradox put forward by Jones [28] which states that "when programs are written in higher level languages, their apparent productivity expressed in source code per time unit is lower than for similar applications written in lower level languages. When software migrates from low level to high level languages, the noncoding tasks act as though they are fixed costs (i.e., specifications, documentation) while the number of source code 'units' goes down. Hence, the cost per unit must go up." However, this is only true if we assume that the total effort in manmonths increases, remains unchanged, or decreases less than proportionally with lines-of-code. It is possible that the decrease in effort involved in coding, testing, and integrating software written in higher level languages is so great that the total development effort is substantially decreased. This would have the effect of counteracting the decrease in the lines-of-code. If we look ahead to Table 9, we see no proof of a lines-of-code paradox in the ESA database even when projects in the same category are considered.

5. As the level of a language increases fewer lines of code are needed to produce a product of the same functionality.

In the ESA database, the difference in the productivity between languages can be accounted for by the five significant COCOMO cost factors (see Table 5). Assembler projects have a low productivity because they have the highest required reliability and storage constraints, high time constraints, and the lowest use of tools and modern programming practices. In contrast, the Ada projects have low required reliability and storage constraints, average time constraints, and the highest use of tools and modern programming practices.

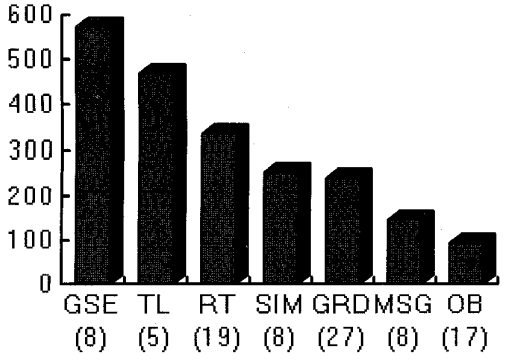
5.2.3 Analysis of Variance by Category

As the categorization of other large heterogeneous datasets [15], [26], [32] have been mainly based on a breakdown into MIS, systems and military projects, with an emphasis on MIS, the results of this part of the analysis cannot be compared with past research and are presented only in order to highlight the existence of low productivity categories in the ESA database. The ESA classification by category alone explained 34% of the variation in productivity. The 99 projects were classified into 10 categories. A subset of 92 projects in categories that had five or more observations was analyzed in more detail. Fig. 4 shows clearly that On Board and Message Switching are low productivity categories. This is due to the fact that the size of the software for most OB projects must be as small as possible. In the ESA dataset, OB projects have the highest time and storage constraints, the second highest required reliability, and the lowest use of tools and modern programming practices. The projects in the MSG category have the highest required reliability and consist of software developed for handling and distributing messages and managing information flows. In some cases, encryption of the messages is required. The high productivity categories, Ground Support Equipment and Tool, have low reliability requirements and time constraints and the highest use of modern programming practices.

5.2.4 Analysis of Variance by Country

Past research comparing the software development productivity levels of different countries is almost nonexistent. Cusumano and Kemerer [15] have published a comparative productivity analysis between the U.S. and Japan in which they find no significant difference in the productivity of U.S. and Japanese projects when the application type, the hardware platform, and code reuse have been taken into account. Jones [27] has published some tables of world-wide productivity

levels but states that there is currently not yet enough accurate *data for such* an evaluation. In the ESA dataset, country as a class variable explained 27% of the variation of productivity. The average productivity for countries with four or more observations is shown in Table 7. These productivity values should not be considered as national productivity levels as they are based on limited observations. Some difference in the mean productivity of the countries in our dataset can be explained by the percentage of projects that companies in each country undertook either in low productivity categories (OB/MSG) or using low productivity languages (COR/AS).



The number in parentheses is the number of observations.

Fig. 4. Mean lines-of-code productivity by category.

Differences can also be accounted for by the mixture of industrial, space and military projects that were undertaken in each country (see Fig. 5). This has also been mentioned by Jones [28] as a factor which influences software productivity at a national level. Belgium appears as the most productive country in our dataset because of the predominance of high relative productivity industrial projects (see Fig. 6). In contrast, the UK appears as the least productive country because of its high volume of military projects. As no other factors considered in our analysis could consistently explain any further difference in productivity across countries, it appears that factors other than the ones considered in our analysis are contributing to productivity differences. Further large scale data gathering efforts are needed to establish the relative productivity levels of European countries and their major influential factors.

5.3 Phase Ib—Analysis of Variance of Individual Nonclass Variables

Of the seven COCOMO cost factors, only five were found to be significant and two, use of tools and modern programming practices, were found to be highly positively correlated. This suggests that in the COCOMO model these two variables could be combined. Referring back to Table 5, we see that the main storage constraint alone explains 53% of the variation in productivity. Low productivity in the ESA dataset is due to high storage constraints, high time constraints, high reliability requirements, low tool use, and low use of modern programming practices.

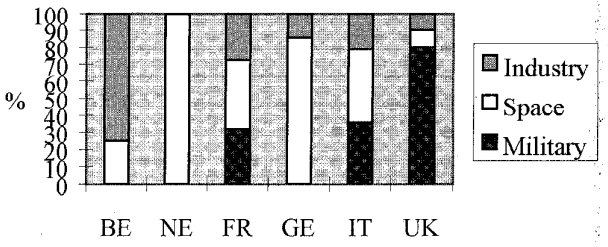
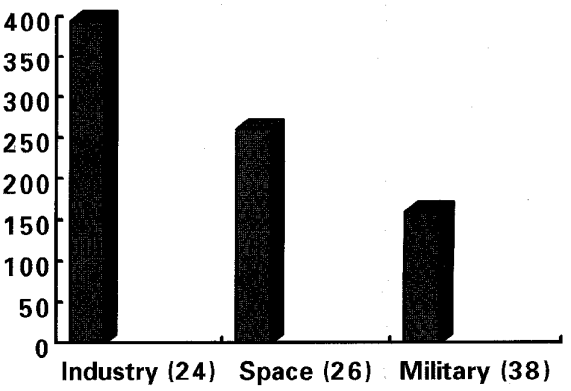


Fig. 5. Breakdown of projects by country and development environment.



The number in parentheses is the number of observations.

Fig. 6. Mean lines-of-code productivity by environment.

These results are, for the most part, in agreement with other researchers. Storage constraints and time constraints were also found to have a negative impact on productivity in the following studies [11], [38], [39]. Boehm [8] assumes that high reliability requirements have a negative impact on productivity in his COCOMO model. However, there does exists a divergence of opinion on the impact of tools and modern programming practices on productivity. In agreement with our results, Jones [26] concluded that the use of tools and modern programming practices improved productivity. Significant gains in productivity due to the use of modern programming practices have also been found by Albrecht [2], Vosburgh et al. [38], Walston and Felix [39], and Brooks [11]. On the contrary, Kitchenham [29] found that no significant

TABLE 7
MEAN LINES-OF-CODE PRODUCTIVITY BY COUNTRY

COUNTRY	NOBS	MEAN PRODUCTIVITY	%OB/MSG PROJECTS	%COR/AS PROJECTS
Belgium	4	838	0	0
Netherlands	6	502	0	0
France	25	419	32	20
Germany	8	406	25	0
Italy	15	365	40	0
UK	34	187	26	29

productivity improvement resulted from the use of tools and modern programming practices. Card et al. [12] determined that although the use of tools and modern programming practices had no significant effect on productivity, the use of modern programming practices resulted in improved reliability. Banker et al. [5] found that these two factors had a negative impact on short term productivity in their study of maintenance projects. Lawrence [30] found that the chief benefits of disciplined programming methodology are experienced in the early design and test stages. He concluded that even though there was no noticeable productivity difference in groups using structured programming or walkthroughs, these factors probably resulted in fewer latent bugs and reduced maintenance costs. As the positive productivity impact of the use of tools and programming methods may not be visible immediately, more research should be done to determine their effect on long term productivity.

Programming language experience was found to have no significant effect on the productivity of the ESA dataset. Kitchenham [29] also found weak empirical evidence that more experienced personnel improved project productivity. Although language experience had the second highest productivity range out of 29 factors studied by Walston and Felix [39], Brooks's [11] analysis of the same dataset determined that programming language experience was not significant for large projects. Boehm [9] included language experience as one of 16 COCOMO software productivity factors, albeit with the smallest productivity range. An analysis by Kitchenham [29] of Boehm's dataset confirms that this result is significant, although she points out that projects with staff of normal experience had similar productivity level to projects with highly experienced staff. This trend was also confirmed by Jeffrey and Lawrence's [22] finding that COBOL programmers did not improve in productivity after a one year experience with the language. The fact that virtual machine volatility was not found to be significant was due to it not varying much among projects. Factor Analysis was also carried out on these seven productivity variables. We found that the seven variables could be grouped in four factors which explained 90% of the variance in the data. The first factor included the variables TIME, STOR, and RELY. The second factor was comprised of MODP and TOOL, the third factor was LEXP, and the fourth factor was VIRT.

The simple models based on TEAM, DUR, and KLOC had a R-squared of less than 0.20 which means that none of these variables alone is a good indicator of productivity. However, the models were significant and as they have been discussed in previous research some comparisons can be made and conclusions drawn.

Productivity was found to decrease with increasing team size. This is probably due to the coordination and communication problems that occur as more people work on a project. Team size explained 19% of the productivity variance with an elasticity[6] of – 0.5. This result is in agreement with the findings of other researchers [10], [13]. In particular, Conte et al. [13] also determined that team size had an elasticity of –0.5 when analyzing projects from the NASA database. Card et al. [12] found that team size was not significant; however, this may be because it was confined to a narrow range in their study.

Increasing project duration was found to lead to a decrease in productivity. Duration explained 12% of the variation in productivity with an elasticity of –0.6. Putnam and Myers [32] include duration with an elasticity of –1.33 in their process productivity equation (see (2)). Their definition of process productivity is directly based on their approach to cost estimation in which they holds that effort varies inversely as the fourth power of development time. This severe penalty imposed by reducing development time is not greatly subscribed to by other researchers [13], nor is it supported by our analysis. In contrast to subsequent findings by other researchers, Aron [1] determined that the productivity of easy and medium difficulty projects of greater than 24 months duration was 66% higher than that of shorter projects. He also found that productivity remained relatively stable for difficult projects no matter what the duration.

Productivity was found to slightly increase with increasing system size for the ESA dataset. This result is the opposite of those of other researchers who have found that productivity decreases with increasing system size [2], [6], [11], [13], [24], [32], [38]. For the ESA database, system size (KLOC) explained 5% of the productivity variance with an elasticity of 0.2. Although Jones found that productivity decreased exponentially and Putnam and Myers found that productivity decreased substantially, Conte et al. found that productivity did not show a strong decreasing trend as system size grew.

5.4 Phase II—Analysis of Variance Models Based on Combinations of Class Variables

5.4.1 Summary

Combinations of relevant subsets of class variables (see Table 4) were analyzed to find the model which could explain the highest amount of productivity variance. Only combinations of two class variables at a time were considered; categorizing the data by three class variables led to too many cells with only one observation. Table 8 summarizes the four best models found:

Although they explained the same amount of variance of productivity, the Category*Language model has more observations than the Company*Language model and can be considered to be better. Therefore the best method of benchmarking the productivity of a project in this dataset would be to compare its productivity to projects of the same category and language.

These results correspond well with the conclusions of Arthur that lines-of-code metrics should only be compared within the same language and to similar projects using identical technologies [3]. He also concluded that lines-of-code productivity is representative only when measured for large projects, as is the case of projects in the ESA database.

6. In this context, elasticity is a measure of the effect on productivity of a change in team size. An elasticity of –0.5 means that if team size is increased by 10%, productivity will decrease by 5%.

TABLE 8
SUMMARY OF ANALYSIS FOR MODELS BASED ON TWO CLASS VARIABLES

CLASS VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL (significance)
Category*Language	80	76%	.58	Log (.0001)
Company*Language	55	76%	.58	Log (.0001)
Country*Category	89	73%	168	Add (.0001)
Company*Category	63	72%	180	Add (.0001)

TABLE 9
MEAN LINES-OF-CODE PRODUCTIVITY BY LANGUAGE AND CATEGORY

Lang/ Category	GSE	TL	RT	SIM	GRD	MSG	OB
Ada	871 (4)*	550 (2)	441 (6)	228 (4)	473 (10)	148 (2)	124 (4)
Pascal	369 (2)	498 (1)	428 (2)		1,064 (1)	287 (1)	67 (1)
Fortran	380 (2)		358 (2)	361 (1)	265 (3)		
LTR			464 (2)		420 (1)		88 (1)
C		380 (2)		424 (2)	206 (1)		178 (4)
TAL					1,064 (1)	125 (3)	
Coral			114 (2)	94 (1)	43 (3)	133 (2)	
Assembler					161 (2)		60 (5)

The number in parentheses is the number of observations

TABLE 10
SUMMARY OF ANALYSIS OF BEST MIXED MODELS

VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL (significance)
Company* subset Category, RELY, TOOL(25%)[7]	30	99%	.16	Log(.0001)
subset Country* subset Category, RELY, TOOL(7%)	54	96%	.26	Log(.0001)
subset Country* subset Category, RELY, MODP(6%)	53	95%	.29	Log(.0001)
subset Language* subset Category, RELY	60	90%	.39	Log(.0001)
TEAM, KLOC, DUR	45	89%	.36	Log(.0001)
RELY, STOR, TOOL(7%)	59	70%	.52	Log(.0001)
RELY, STOR, MODP(7%)	59	70%	.53	Log(.0001)

5.4.2 Analysis of Variance by Category and Language

Table 9 shows the average productivity of projects of the same category and language. It can be concluded that no matter what language is used, the categories of On Board and Message Switching have a low productivity. In addition, the languages Coral and Assembler have a low productivity regardless of the category in which they were used. The low average productivity of the language TAL in the ESA dataset (Fig. 3) appears to be a result of its being used for Message Switching projects.

7. The number in parentheses is the amount of productivity variation explained by MODP or TOOL.

5.5 Phase III—Models Based on Combinations of All Variables

5.5.1 Summary

Multivariable models were run to determine if maximum team size, the duration of the project, the system size (KLOC), and the seven COCOMO factors grouped together, as well as combined with subsets of class variables which contained a sufficient number of projects at each level, could better explain the variation in productivity. The variables MODP and TOOL were found to be significantly correlated at the 0.81 level and thus were not considered together as independent variables in the multivariate regression. Table 10 shows the amount of variance explained by the best models.

Taking into account the number of observations, the best mixed models, both of which explain 95% of the productivity variance, are based on the class variables: Country and Category, and the variables: required reliability and either use of tools or modern programming practices. This suggests that for a given Country and Category, productivity can be improved by increasing the use of tools and modern programming practices. However, these models based on country are misleading because there are not enough observations in each country to make this categorization reliable. It is for this reason that the model based on Language and Category is also presented. Although is explains less of the productivity variation, it makes more sense.

The best nonclass variable model of lines-of-code productivity was found to be based on team size, duration, and KLOC. However, we will ignore this model because it is roughly the definition of lines-of-code productivity and thus adds nothing to our knowledge. The two models based on required software reliability, main storage constraint and either use of tools or modern programming practices are much more interesting. As the required software reliability and main storage constraint are fixed, we can conclude that the use of tools or modern programming practices are major factors in productivity improvement. However, as the use of tools and modern programming practices are highly dependent on the language used, they are only controllable to the extent that the choice of language is not imposed. It is interesting to note that once language is added to the model neither tools or modern programming practices are significant.

5.6 Phase IV—Comparison of Lines-of-Code Productivity and Process Productivity

Putnam and Myers [32] maintain that process productivity is superior to simple lines-of-code productivity because it covers a complex set of factors affecting the entire software development organization throughout the development process including: management practices, use of methods, level of programming language, software environment, skills and experience of team members, and the complexity of the application type. According to Putnam and Myers, process productivity can be used to measure the effectiveness of an organization over time, to compare the effectiveness between organizations, or to indicate the degree of complexity of the application work being done. In order to assess the added value of process productivity, a detailed analysis of the factors affecting process productivity in the ESA database was undertaken in this phase of our analysis.

5.6.1 Summary

The single variable which explained the greatest amount of variance (60%) of process productivity in the dataset was Country. The results of analyzing only subsets of class variables where each level contained a sufficient amount of projects substantially effected the results with the classes subset Language and subset Category becoming insignificant. In addition, limiting Country to the six countries containing four or more projects caused the amount of variance explained by Country to decrease from 60% to 17%. Process productivity was not found to vary significantly with environment. A summary of the analysis can be found in Table 11.

Models were also run to determine if maximum team size, the duration of the project or the system size (KLOC) could be used to explain some of the variation in process productivity. In addition, analysis was carried out on a subset of the ESA database which included data for the seven COCOMO cost drivers. Table 12 shows the amount of variance for each variable individually.

Of the set of complex factors which are supposedly covered in the definition of process productivity, we are able to

TABLE 11
SUMMARY OF PROCESS PRODUCTIVITY ANALYSIS OF INDIVIDUAL CLASS VARIABLES

CLASS VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL (significance)
Country	57	60%	3,918	Add(.0001)
Language	57	53%	4,571	Add(.0005)
Category	57	45%	4,695	Add(.0002)
Company	46	34%	3,709	Add(.0554)
subset Country	54	17%	.88	Log(.0505)
subset Language	46			not significant
subset Category	53			not significant
Environment	53			not significant

TABLE 12
SUMMARY OF ANALYSIS OF INFLUENCE OF NONCLASS VARIABLES ON PROCESS PRODUCTIVITY

VARIABLES	NOBS	VARIANCE EXPLAINED	ROOT MSE	MODEL (significance)
STOR	23	34%	.75	Log(.0034)
KLOC	57	32%	4882	Add(.0001)
TOOL	24	17%	.83	Log(.0440)
VIRT	23	16%	4694	Add(.0561)
DUR	57	15%	.94	Log(.0030)
TEAM	45			not significant
RELY	53			not significant
TIME	53			not significant
MODP	23			not significant
LEXP	24			not significant

look in particular at the effect of the use of methods, level of programming language, software environment, experience of team members, and company differences on process productivity. Looking in detail at Tables 11 and 12, we see that environment, experience of team members and modern programming practices had no significant effect on process productivity in the ESA database. Furthermore, the difference in the level of programming language and category in subsets in which there were an adequate number of observations at each class level was not significant for process productivity. The difference among companies did account for 34% of the variation in process productivity; however, company differences accounted for 53% of the variation of lines-of-code productivity.

In summary, we believe that process productivity is not superior to lines-of-code productivity for the following reasons: First, the utility of incorporating duration in the definition of productivity is questionable as it is one of the factors which accounts for the least amount of variation in lines-of-code and process productivity. Second, lines-of-code productivity already covers a complex set of factors affecting the development process such as the differences among company, language, category, environment, storage and time constraints, use of tools and modern programming practices, and software reliability requirements. The variation of these factors have significant effects on the variation of lines-of-code productivity while many of these factors were not found to be significant for process productivity. Finally, lines-of-code productivity is easier to calculate.

6 Conclusions

The objectives of this paper were first, to provide significant and useful information about the major factors which influence the productivity of European space, military, and industrial applications, and second, to compare two productivity metrics, process productivity and lines-of-code productivity, in order to determine which metric was better at measuring the productivity of projects similar to those in our dataset.

Our study has found that organizational differences account for most of the productivity variation of projects in the ESA dataset. This highlights the need for companies to establish their own software metrics database in addition to benchmarking their data against that of other companies. The results indicate that some companies are obtaining significantly higher productivity than others. Some of the difference in productivity among companies can be attributed to their use of low productivity languages, such as Coral and Assembler, or to the fact that many of their projects were in low productivity categories, such as On Board and Message Switching; however, some differences must also be due to the ways in which these companies manage their software development projects. Further research should concentrate on identifying which management related factors contribute to productivity improvement. In addition, high productivity was found in those companies which undertook projects with low reliability requirements, low main storage constraints, low execution time constraints and which had a high use of tools and modern programming practices. As the first three requirements are fixed, this suggests that the use of tools and modern programming practices are major controllable factors in productivity improvement.

We have also been able to contribute to knowledge in the area of software development productivity by confirming or disproving the applicability of previous research results to projects in the ESA dataset. In agreement with most other researchers, we have found that productivity decreases with increasing storage constraints, timing constraints, reliability requirements, team size, and project duration. We have also found that programming language experience has no significant effect on productivity. As the conclusions of previous research are divided over the positive impact of the use of tools and modern programming practices on productivity, and as the benefits of these two factors may not be visible immediately, more research should be done to determine their effect on long term productivity. Contrary to the findings of other researchers, we have found that productivity increases with increasing system size and that high level languages do not appear less productive than low level languages when measuring productivity in lines-of-code.

Finally, we have determined that, for the ESA database, the process productivity metric is not superior to the lines-of-code productivity metric. Until the use of a better metric becomes widespread for non-MIS applications, the best measure of relative productivity for space, military and industrial applications is lines-of-code productivity.

The relevance of any analysis is greatly limited by the quality of the data available. One of the weaknesses of the ESA database is that no faults data was collected and thus there is no means of assessing the quality of the projects. The analysis would also have been much more meaningful had metrics concerning management factors been collected. Before any data collection effort, the hypotheses to be tested should be formulated, terms should be precisely defined, and care should be taken to ensure that the scales used to collect the data support statistical analysis. The ESA questionnaire has now been modified to these criteria.

The ESA database is being maintained at INSEAD. A sanitized version of the database is available to any company who provides data.

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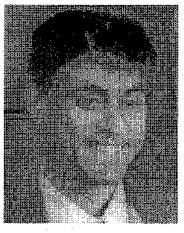

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