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Programme Management Monitoring and Controlling: statistical predictive models to improve Estimate at Completion

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ABSTRACT

Programme Management plays a crucial role in successfully executing a group of related projects which together achieve a common purpose in support of the strategic aims of the business. Effective monitoring and controlling activities in the context of a programme are essential to ensure adherence to budget and schedules. Forecasting cost estimate at completion is a fundamental aspect when managing a group of projects in a coordinated way. The thesis focuses on the development and implementation of statistical linear predictive models to enhance cost estimation accuracy and precision in comparison to the most widely used index-based methods, thereby enabling more informed decision-making, proactive cost control, and practical implementation guidance. The research begins with a comprehensive review of existing literature and practices related to project and programme management, cost estimation, and statistical predictive modelling. The already existing approaches and examined techniques are helpful for developing the necessary methodology framework whose dimensions will be applied to a 10-projects porgramme case-study belonging to the software testing IT practice. To this end, the projects under examination have been firstly described and three EVM datasets created to analyze the full programme observations and, in addition, two of its subcategories determined by projects' division in relation to allocated teams. Firstly, correlation analysis have been conducted to initially assess the relationships between variables and testing PMO's hypothesis. Next, multiple linear regression analysis are performed. The shrinking and regularizing LASSO selection procedure was used to determine the number of regressors over twelve initial candidates for each of three scenarios, whereas the general linear model tests the overall statistical significance and calculates parameters estimates. Finally, accuracy and precision of the fitted models have been assessed by the Mean Absolute Error and Standard deviation against seven index-based forecasting methods resulting to be always the top-ranked. By looking at the diagnostics of fit, considerations on the three models' consistency are presented too. The thesis concludes with outlining limitations and hints for future research.

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INTRODUCTION

Programme Management plays a vital role in the successful execution of a collection of interconnected projects that collectively share and wants to achieve common objectives in alignment with the strategic goals of a business. It is crucial to effectively monitor and control activities within a programme to ensure adherence to budgets and schedules. When managing a group of projects in a coordinated manner, forecasting the estimated cost at completion is a fundamental aspect. This thesis focuses on the development and implementation of statistical linear predictive models to enhance the accuracy and precision of final cost estimation, overcoming the most known and used index-based methods. This improvement enables more informed decision-making, proactive cost control, and practical implementation guidance.

The research begins with an extensive review of existing literature and practices in project and programme management, cost estimation, and linear and nonlinear statistical predictive modeling developed by many authors. The methodologies and techniques examined in prior studies provide valuable insights for developing the new framework which will be applied to a case study of 10-project programme in the area of software testing IT practice. The thesis describes the programme and its embedded projects and creates three Earned Value/Earned Schedule Management datasets necessary to develop the predictive models able to improving Cost Estimate at Completion $(CEAC)$. The proposed models consider the entire programme dataset to firstly determine a generalized applicable formula, furthermore, two of its subcategories based on projects' division in relation to allocated teams are individually analyzed with the aim of understanding which variables affect the most each team.

Initially, correlation analysis is conducted to assess the relationships between features and test the programme PMO's starting hypothesis. Subsequently, multiple linear regression analysis is performed. The shrinking and regularizing LASSO selection procedure has been employed to determine the optimal number of regressors from an initial pool of twelve candidates in each of the three scenarios, whereas the general linear model tests the overall statistical significance and calculate parameter estimates.

Finally, the accuracy and precision of the fitted models were assessed by using the Mean Absolute Error and Standard Deviation, comparing them against seven index-based forecasting methods. The outcomes show how the new methodology outranks the traditional approach in all the three described scenarios. The thesis also presents an examination of the fit diagnostics and discusses on the models' consistency. It concludes by outlining limitations and suggesting directions for future research.

CHAPTER 1. LITERATURE REVIEW

1.1. Project, Programme and Portfolio Management

Over the last decades the interest of various certification bodies (such as Axelos, PMI and IPMA), academics and professionals to better develop on standards, procedures, processes, and individual competencies required in the project, programme and portfolio management has been largely rising. The fact of having common guidelines and approaches established by recognized bodies is always beneficial for the ones working in project-oriented environments (3PM). They represent certain rules and norms to be followed which explain how to conduct activities in order to reach a desired result being the optimum in a given context (Eskerod and Huemann, 2013).

The IPMA ICB 4.0 gives an interesting contribution in examining what are the main competencies area required in the 3PM that are summarized in: People, Practice and Perspectives. Its goal is to present distinct key indicators for each environment to be able to assess the individual output performance. This is just an example of how important the understanding of the three environments (project, programme and portfolio) has become more and more crucial in addition to the already existing and acknowledged processes, methodologies and tools embedded in the standards applied by practitioners.

Nowadays the Project Management is a very well-known and implemented discipline. The PMBOK (Project Management Body of Knowledge) defines it as the way of planning, organizing, and controlling resources to achieve specific objectives within a defined timeframe and budget. It involves applying knowledge, skills, and tools to execute projects effectively and efficiently. It starts with the definition of its scope and objectives, and it ends with its closure when all the deliverables have been completed and the handover to stakeholders or clients is going to take place (Lock, 2008).

Although the management of single projects seems to be clear to companies and institutions, the “Programme” is still a concept that counts of different interpretations up to the context, the sector and necessities linked to grouping of projects (Gray, 1997). A programme is intended as a group of related projects which together achieve a common purpose in support of the strategic aims of the business (Project Management Handbook). The activities are centralized and coordinated in order to achieve strategical objectives within a firm. A programme approach should be focused on the management of interdependencies between the various embedded activities and its success is measured based on its ability to realize and deliver the foreseen benefits to the organization (PMI,2009).

Gray (1996) purposes two models that might be encountered when dealing with programmes:

- The loose-open model:
  It is a purely nominal umbrella able only to group already existing projects managed quite independently from each other. The sole advantages stand on having the possibility of aggregate reporting and high-level overviews. The ownership remains in the hands of the project stakeholders. It is barely created to provide to the project managers easier access to activities status and deliverables, thus sound decision can be undertaken even though is it not necessarily needed a centralized management. The value added here is the improved information flow.
- The strong model:
  Without a coordinated way of managing the group of related projects it would not be possible to gain any benefit. Independency between activities is discarded. The establishment of a governance authority is fundamental, usually defined as a programme control body. Form this mission the belonging projects are defined, each of which must contribute to the achievement of the final strategic goal.

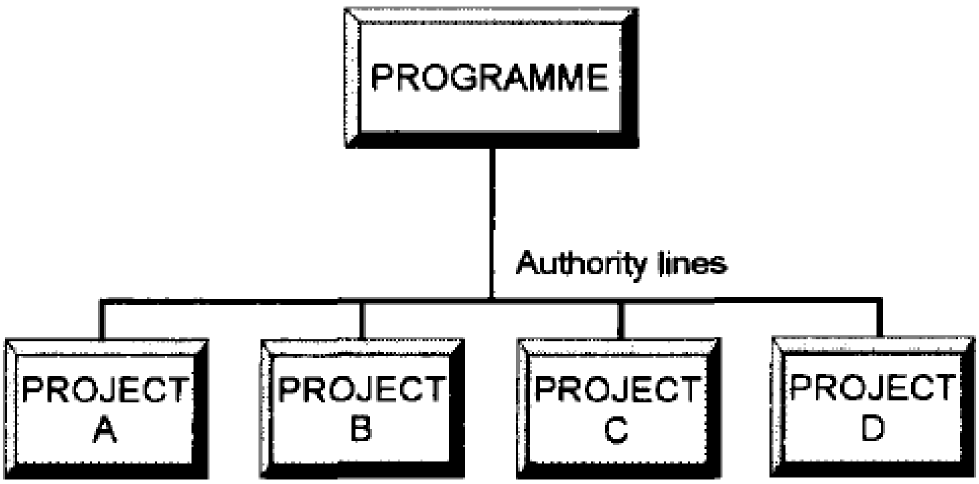

Figure 1 - Strong programme model
(Source: Gray, 1996)

In terms of inter-relationships between overall program, embedded projects, subprojects, and work packages the model describes three possibilities:

- Vertical -> The hierarchy is evident, and the model is a strong type. Reporting communication flow and escalation have well known paths.
- Horizontal -> The horizontal form of projects and activities relationship exists regardless from the fact that a vertical structure has been recognized. It relies on interactions and interdependencies between projects. In weak structures, individual activity managers rely on their own arrangements for managing interactions. Success depends on their commitment and access to relevant information. If instead a verticality is present, the established authority of the higher levels can act in any case to regulate transactions, solve impediments and conflicts at the horizontal level.
- Transverse -> The transverse relationships happen between single activities involving two sub-types: alpha and beta. The former means grouping similar projects from different hierarchies and specialists that accept workloads from variety of sources, while the latter means assimilating a project into the operational work of a functional unit (the so called "business as usual"). Both sub-types can weaken or eliminate the original project structures, causing difficulties to the true project owner and people that misunderstand which are the work assigned, their priority and effort required.

The study ends emphasizing the fact that if a programme is in place, hierarchy are fundamental and critical at the same time. Level of seniority should be clear to all figures involved. Moreover, there is the need of effective interchange of information between allocated resources and their responsible. The right technologies and capabilities should be employed to reach the strategic goals. When these prerequisites are assured before entering into subcontracting arrangements, then there will be more chances to well perform as a three-dimensional matrix operational framework where any given project, work or activity type is subject to vertical, horizontal, and transverse alignments in the context of the overall work to be done.

Having clarified the possible structure of a programme it is dutiful to distinguish the former from the last possible environment represented by the 'Project Portfolio'. The portfolio includes projects, programmes and other work managed as a cohesive unit with the aim of maximizing organizational value (PMI,2017). It focuses on establishing a centralized management thanks to which the identification, prioritization, direction, and control of its components is facilitated in order to achieve long-term targets associated with market positioning, business growth, and to share value between shareholders and stakeholders (Munson and Spivey, 2006). In this way a particular attention is given to the optimization of resource distribution between projects, and ensuring collaborations among stakeholders (Archer and Ghasemzadeh, 1999). The PMI stresses that Portfolio Management can be applied to diverse context and environments, public or private, where the full life cycle is planned, executed, and monitored. To define the company's strategic objectives, project portfolio has the purpose of:

- Aligning programs and projects to reach top management's strategic goals
- Evaluating and prioritizing the components and the possible portfolio's risks
- Benchmarking components within the programs and projects
- Road mapping and long-term scheduling for the selected programs and projects

A very interesting contribution that highlights the importance of resource allocation optimization solutions in project portfolios is the one of Ronald Klingebiel and Christian Rammer (2014). The authors emphasized strategies in innovation portfolios given the uncertainty and potential for failures. It has been found that the better the allocation, the higher the company's performance and the more innovative the level reached, especially for novel product producers and service companies.

Thereby, the management of the three environments is getting more and more fundamental for companies and organizations, private and public, and it plays a vital role in any nowadays business.

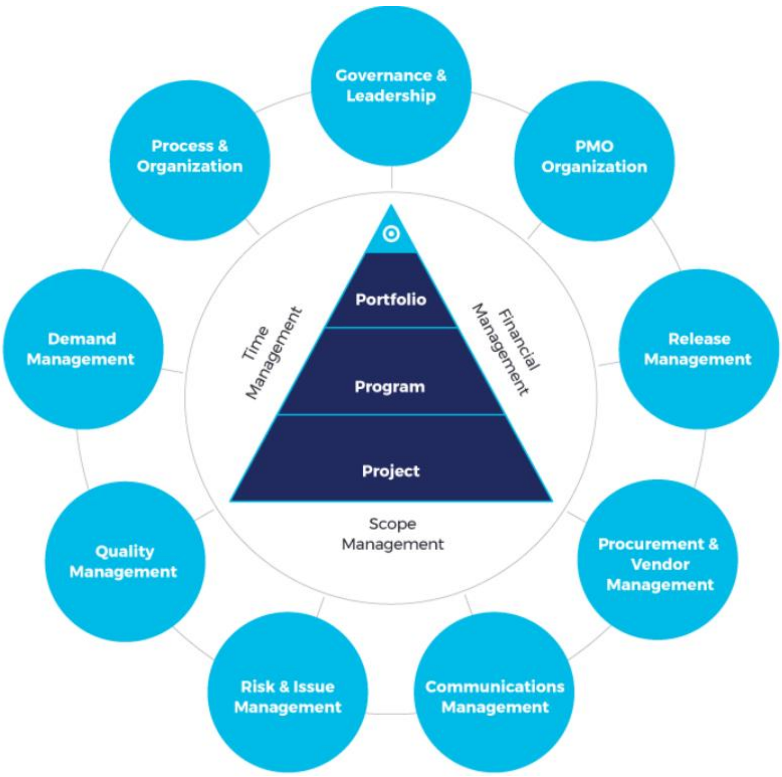

Figure 2 - Project, Programme and Portfolio Management (Source)

1.1.1. Zooming on Programme Management

The multiple project environment is a set of interrelated efforts at different levels of the organization: the Project Management Team is responsible for a single project, a group of similar projects is held instead by the Programme Management staff, and a collection of programmes, the so-called portfolio, is in charge of the Corporate Top Management (De Marco, 2018).

The PMI (2016) cites that a programme is formed by group of related projects with the necessity to be managed coordinately in order to obtain benefits that would be unavailable if managed individually. It can be said that it is a structure of medium- and long-term activities of at least two or more related projects. Usually the Project Management Office (PMO) is responsible for the management of a program, and, in many cases, a Programme Manager might be appointed. These entities perform planning, controlling, and directing activities for all the embedded projects.

The challenges arising from the multiple-project environment are influenced by factors such as the organization's complexity, size, and role. These challenges stem from distinct market orientations, diverse nature of projects, resource constraints, and competition among projects (Archibald, 2003). Hence, programmes definition and establishment can be determined by client, size, complexity, or by product type. Anther very often situations is the division by delivery system such as Fixed Price or Time and Material that determine the necessary processes, standards, and skilled resources necessary to implement. The procurement constraint is crucial for the contractor to understand what the risk is to be hold and the level of monitoring and controlling to be applied while completing the activities.

In the corporate sector, once the executives have divided and selected projects in value-oriented programs looking at the strategic objective within the firm, the Programme Management staff is going to work on gathering the opportunities and provide best practices to manage all the activities. The strategic goal can only be reached if each project manager or project leader successfully complete his/her projects. The institution of the programme is there to fill the gap created between corporate strategy and execution of each single project (Archibald, 2003). To this end, centralization is required through the PMO for the planning, scheduling, monitoring, and reporting by using standardized tools and processes. Centralized management of resource allocation and capital allocation is also in the forefront to create efficiencies among the components and establishing communication interfaces between organization’s levels.

When managing in a coordinated way, it is important to remember that the project is a contract and parties are called to respect the designed time, cost, and quality. Program

Managers have the responsibility to stay within the expected expenses and make the project returns match the foreseen profits.

1.2. The Project Management Office

At operational level, for both programmes and portfolios, it is essential for firms and organizations to use performance metrics and reports that can track period by period for all single embedded projects their progresses and status in order to ensure that they satisfy the established objectives (Hoon Ko and Kim, 2019). The stakeholders have the need to easily and intuitively interpret the financial situations, risks and problems encountered. In turn, the potential value prioritization and analysis of the set of projects in programmes and portfolios is going to be facilitated through the monitoring of return on investments, cost reduction and project success rate (PMI, 2013). This is the reason why from the mid-1990s on, a huge growth in Project Management Offices (PMOs) has been recorded (PM Solutions, 2016). The PMO is defined as the one is in charge of standardizing the project management system at the enterprise level, accumulating project experience, providing the needed know-how and opportunities for education and training, so that the overall efficiency is enhanced (Dinsmore, 1999). Organizational change and quality management are other aspects in the interest of the office that has to have the ability to adopt and integrate these features within the firm (Sidhu, 2015).

Kwak and Dai (2000) defines the PMO as an independent organization held by its full-time employees who provides technical and administrative services, training, and mentoring. They emphasized, alongside various other authors, that its role does not only count in the monitoring and control, but also in the establishment of strategic, operational, and tactical objectives and guidelines to teams.

Even if many academics and authors tried to give their individual PMO definition, it is important to stress that its role is evolved from the management of a single project in a specific business unit to the arrangement of the whole programme or portfolio in a centralized manner at a company level. Nowadays it is not intended as the people that control schedule and budget of a sole work, but rather as the ones that improve the contribution of projects in achieving corporate's business performance (Hoon Ko and Kim, 2019). Indeed, studies have shown how the PMO efficiency positively affects the maturity of project portfolio management and how well it aligns with the business goals. A summary of the main PMO's activities is reported in the Figure 3.

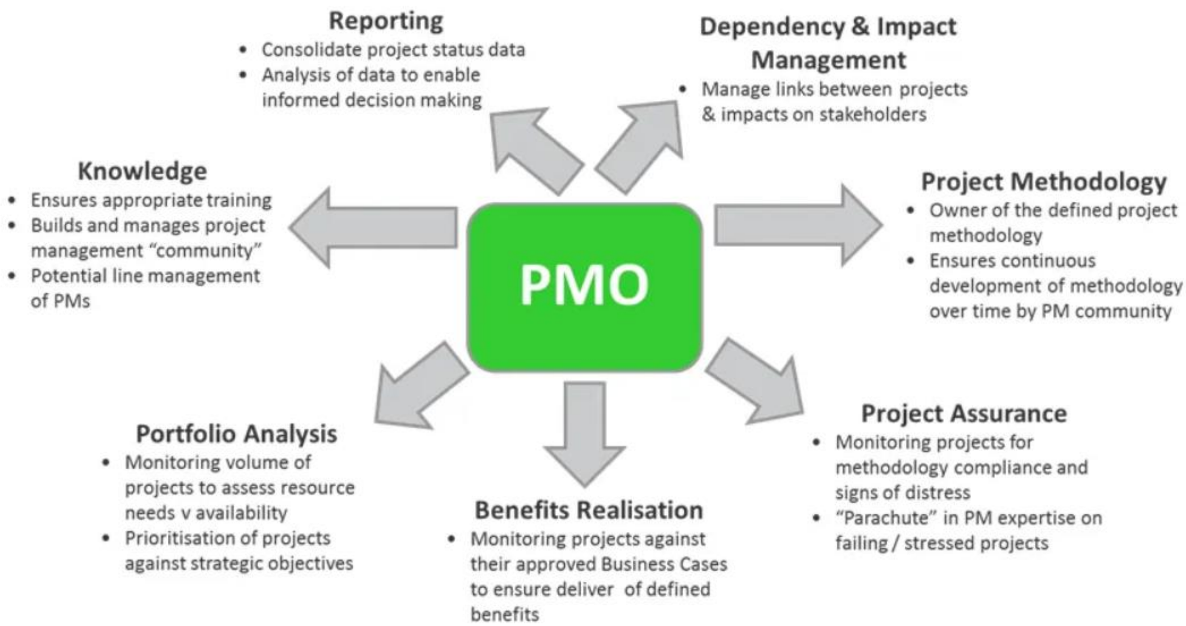

Figure 3 - PMO's best practices
(Source: bestofmvm.wordpress.com)

1.3. Monitoring and Controlling

One of the most important activities performed by the PMO is the monitoring and controlling of projects. This phase in characterized by reporting the various project progresses and statuses that allows project managers and stakeholders to detect possible incurred problems and to undertake eventual corrective actions with the aim not to deviate from the initial established time, cost, and quality (De Marco, 2018). In case one of these 3 elements of the triangle changes, also the others will be affected. Therefore, before performing monitoring activities, it has to be verified that the scope of work stays univariate for the entire project duration. If the scope instead varies due to client change orders, it is fundamental that before proceeding with the internal measurements, the rescheduling has been carried out and the baseline updated.

With the aim of establishing the measurement system, metrics and performance indicators are used to identify deviations with respect to the baseline that can impact on time and cost at completion. The monitoring and control are both on the single project, to evaluate its contribution to the overall, and on the aggregate to analyze how the combinations impact on the system (Ottaviani, 2019).

While the monitoring is defined as the set of procedures and practices necessary to collect information of the achieved performances and is based on the adoption of various performance metrics (able to detect variances), the controlling is focused on adjusting projects to meet desired final goals (Hazır, 2014). The control includes decisions, actions and changes aimed at bringing the project back aligning it to the plan. It is carried out in real time, usually during the execution when is still possible to tackle issues at an affordable effort. Therefore, monitoring and control are both part of a feedback system.

Finally, this process makes the exchange of information between PMO/PM and stakeholders thanks to which is much easier to meet the latter needs and expectations.

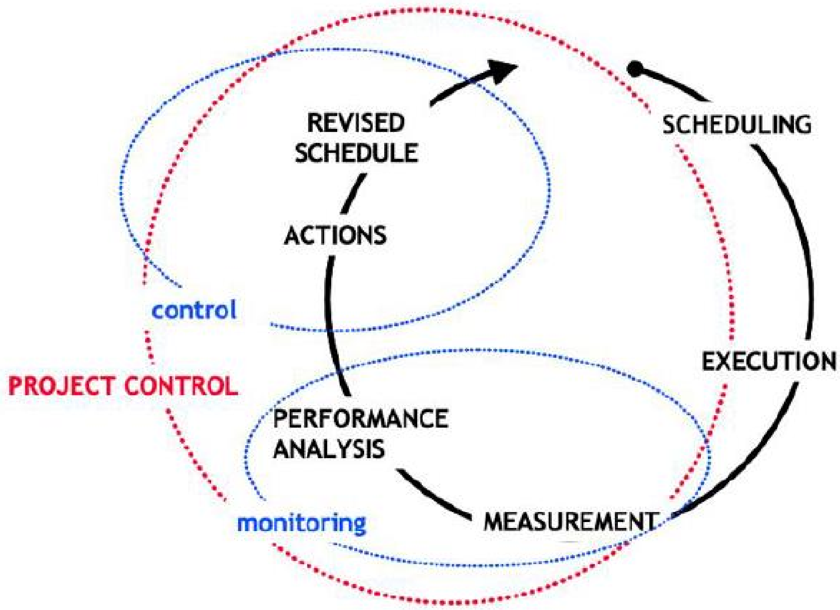

Figure 4 - Project control as a part of a feedback system
(Source: De Marco, 2018)

1.3.1. The Earned Value Analysis

The Earned Value Analysis is the most spread methodology to monitor and control projects and it is based on monetary units to measuring and communicating progresses at a certain point in time (Sackey et al., 2014). The major strength of the method is to consider not only the actual cost against the scheduled one, in fact the performance metrics are compared also involving the work performed and corresponding estimated earned value. Cost and schedule variance are calculated to evaluate the status and predict total project cost and duration (Hazir, 2014). This is essential in the optic of overcoming uncertainty and risks that often cause delays and overruns, that is the reason why forecasting methods should be used during the project executions to well predict these values (De Andrade et al., 2019). Vandevoorde and Vanhoucke (2008) and many others have attempted to go deeper and develop forecasting methods based on EVA to improve forecasting power. This point will be better developed in the next paragraph.

A multitude of books and references, many of which are reported in the bibliography of this dissertation, give the possibility to point out a comprehensive recap of the main principles and assessment criteria embedded in the EVA. The latter can be applied regardless the project type. The values are:

- Planned value (PV) or Budget Cost of Work Performed ($BCWS$):
  It represents the planned cost to accomplish the work scheduled in the timeframe taken into consideration as a standard against which performances are compared with the aim of detecting deviations. The formula is:

$$BCWS = Budget\ cost * work\ schedule$$

- Budget at Completion (BAC):
  It is the total planned value for performing the whole project.

- Actual Cost (AC) or Actual Cost of Work Performed ($ACWP$):
  It gives the measurement of the effective borne expenditures in the given period. It is calculated by:

$$ACWP = Actual\ cost * Work\ Performed$$

- Earned Value (EV) or Budget Cost of Work Performed ($BCWP$):
  It allows to incorporate the information of the project progress at a specific point in time since it lacked in the previous measures, to be able to get the budgeted value of work completed to date (with $PV\ and\ AC$ is only possible to depict the accounting discrepancy between what has been originally planned and the actual incurred). The equation is:

$$BCWP = Budget\ cost * Work\ Performed$$

Therefore, it is possible to compare $BCWP$ with $ACWP$ to calculate cost deviances, and $BCWP$ with $BCWS$ to obtain schedule discrepancies. The way of determining the Work Performed in term of percentage depends on the project type, in this regard an example is provided in the following methodology chapter which considers a selected case study to pursue an empirical investigation.

Moreover, the parameters can be graphically represented with S-curves for an easier interpretation. On the x-axis the variable is the time and on the y-axis the variables are the cumulative $AC, EV, and\ PV$. The AC cumulates as the project goes on and effective cost are registered, the second cumulates alongside the project status, the latter, instead, is initially established and remains as is. The S-shape is due to:

- Early stage: the project growth and its execution are limited by the initial set up phase so that the curve does not heavily inflate.
- Middle stage: the progress is much faster to progress due to the execution phase in which most of the effort is registered until its maximum at the 'point of inflection'.
- Late stage: the growth starts to decline, the S-curve reaches the upper asymptote, and the project enters to its mature phase. Usually most of the work has been already done, only secondary tasks are carried out such as reporting, reviews and approval activities.

The possible S-curves scenarios are reported in the below picture. The most unfavorable scenario occurs when the project experiences both budget overrun and schedule delay. This scenario is depicted in the $A1\ graph$, where cost-related issues are more prominent, and in the $A2\ graph$, where schedule delays are more significant. Conversely, the best-case scenario arises when the project achieves cost savings and is ahead of schedule. This situation is illustrated in the $C1\ graph$, where cost performance is better than scheduled, and in the $C2\ graph$, where schedule duration outperforms cost expectations.

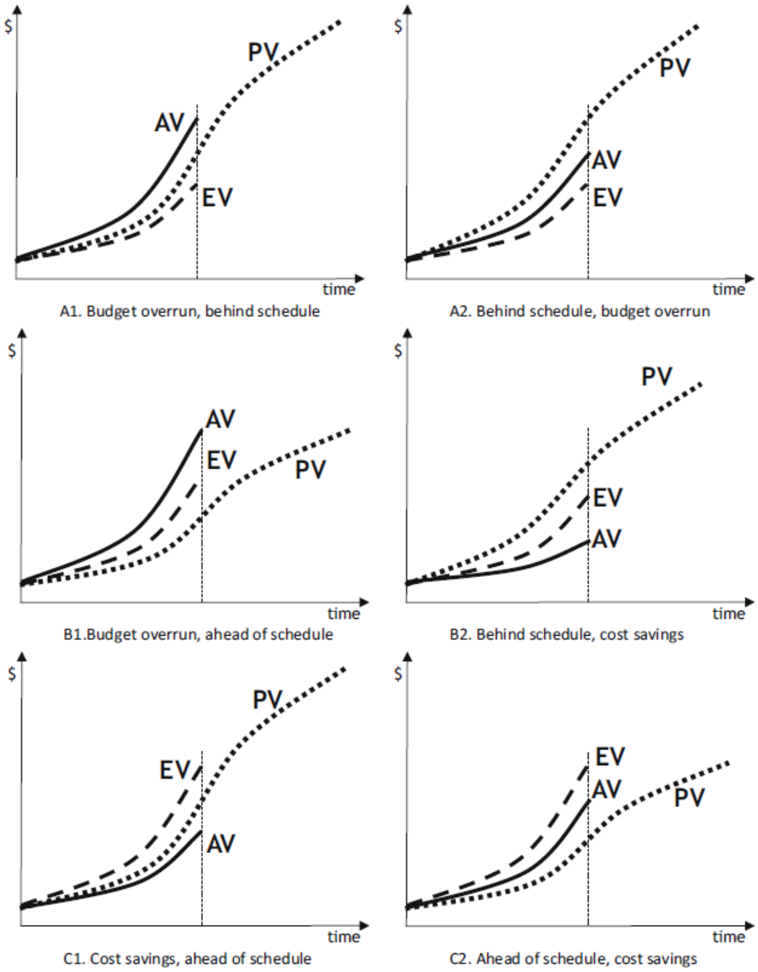

Figure 5 - S curves scenarios
(Source: De Marco, 2018)

Having the structure of the graphs in mind, it is possible to conduct the variance analysis for attaining the exact monetary values of positive or negative statuses and related indexes which measure the observable performances in percentage terms. The variances and indexes are listed in the following:

- Resource Flow Variance (RV) and Resource Flow Index (RFI):
  The first one is a metric that assesses the variance between the presumed expenditure and the actual expenditure within a specific period, irrespective of the quantity of work completed. A negative RV value indicates a project overrun, a positive value signifies a project underrun, and a value of zero indicates that the project is on target. In term of RFI a value greater than one stands for resource allocation efficiencies and a correct initial estimation of the required efforts, instead, when lower than one, it depicts a situation of inefficiency compared to the baseline. A value exactly equal to one means being on target. It is important to underline that these parameters do not always indicate a positive or negative scenario, since the

progress are out of scope: a project can go faster and cheaply than how it could have been expected or slower and more expensively than expected. Here the corresponding formulas:

$$RV = BCWS - ACWP$$
$$RFI = BCWS/ACWP$$

- Cost Variance (CV) and Cost Performance Index (CPI):
  CV expresses a comparison between the budgeted cost of work performed with the registered actual cost. A positive value means the project is underrun, with a gain of value. A negative variance means the project is over budget with a loss of value, value equal zero means the project is on budget. In turn, the index CPI of less than one means project overrun, while a CPI more than one indicates a budget underrun. The expressed formulas are:

$$CV = BCWP - ACWP$$
$$CPI = BCWP/ACWP$$

- Schedule Variance (SV) and Schedule Performance Index (SPI):
  They monitor the difference between the Budgeted Cost of Work Performed and the Scheduled one, meaning comparing how much work has been achieved in that specific period with the one planned to be achieved. If the SV is negative, it indicates that the project is behind schedule, a value of zero suggests that the project is exactly on schedule, while a positive SV indicates that the project is ahead of schedule. Similarly, an SPI less than one indicates a project is behind schedule, a value of zero indicates the project is on schedule, and a value greater than one indicates the project is ahead of schedule. The equations are reported below:

$$SV = BCWP - BCWS$$
$$SPI = BCWP/BCWS$$

The EVA is a very practical and popular tool, in fact during the last decade more and more organizations have been implementing it for conducting monitoring and controlling activities. However, criticisms on the limitations of the analysis have been outlined too. Hall (2012) says that in the EV practice the critical and noncritical activities are not treated differently and that they are assumed to be independent on each other. What is more, the quality of processes and their outputs are not assessed plus information requirement is high and sometimes companies, especially the small and medium ones, might not have the capability to introduce training on the job. It should be considered that these kinds of structures not always can afford the employment of a full-fledge PM Office. Rozenes et al., (2004) stress that, depending on the sector, the variables of time and cost might not be sufficient to explain the project status, thus other performance indicators are needed such as technical, operational, and quality based. They proposed a multidimensional control system to monitor the work breakdown structure (WBS) from a work package point of view.

Another important critic has been made on evaluating schedule performance expressing it in monetary values. The dissertation deeper develops on this in the next section.

1.3.2. The Earned Schedule Approach

Walt Lipke (2004) has been one of the first academics expressing concerns on the traditional EV methodology. He underlined how the EVA schedule indicators fail to provide good information over the final third of the project and completely break down when execution goes on over its past planned completion date. As soon as the project approaches its end date, the SV tends to zero because the amount of WP gets closer and closer to the WS for completion, in turn the value of SPI is going to get to 1. In this way, there are no chance to observe schedule deviations even when it is definitive that the program is not finished on time. To this end, an SV equal to 0 or SPI equal to 1 could signify that the task is completed, but also that it runs sticking to the plan (Vandevoorde and Vanhoucke, 2005). What is more, the schedule variance is measured in monetary term rather than time and this might mislead project and programme managers. The Earned Schedule approach was developed to overcome these issues.

The Earned Schedule method allows to track forwards or backwards the Earned Value (EV) to the Planned Value (PV) at a point in time (when the review is performed). On the x-axis (the time axis) the intersection is going to be read in order to compute the

ES value. Hence, the ES can be found by knowing in which time increment of PV the EV occurs. ES, expressed in time increments, is the real time performance that is compared to the expected one. Mathematically the concept is expressed by the formula below, where c represents the time units for which EV is greater or equal to PV.

$$ES_t = c + \frac{EV - PV_c}{PV_{c+1} - PV_c}$$

Having determined the ES value in time units, it is now possible to express the performance parameters $SV \; and \; SPI$ in time units too.

- Schedule Variance $SV(t)$:
  The $SV(t)$ can be greater or lower than zero and indicates the number of time units that the project lags or advances its expected performance. In this case it represents the real time difference at completion being equal to 0 only if the project is really on time. The $SV(t)$ is represented by the difference between the ES and the Actual Time:

$$SV(t) = ES - AT$$

- Schedule Performance Index $SPI(t)$:
  It is the ratio defined as the value of ES divided by the actual time:

$$SV(t) = ES/AT$$

Lipke's findings have been tested and proved by many other authors. For instance, Henderson (2003) applied the new method to a portfolio dataset composed by projects and subprojects. He concluded that ESA showed better forecasting accuracy than the traditional EVA and simultaneously confirmed the strength of the new metrics whose behaviors are correct over the entire elapsed. Rujirayanyong (2009) also checked the validity of Lipke's statements that turn out to be one more time confirmed in his analysis called *'A comparison of Three Completion Date Predicting Methods for Construction Projects'*. On one hand the improvement made by the ES approach applied to major defense programs in United States are emphasized, on the other hand, the necessity of the analysis to be complemented by the EV cost metrics is reminded too. Even Lipke (2011) himself comes back to the potential drawbacks of his model especially present in small and short duration projects. The ES indicator and duration forecast might be worsened in these cases by "down-times" – periods lacking scheduled activities – and "stop-work" – execution periods for which the management has stopped performances. However, the applicability of the ES implementation stays univariate for any type of project (Vanhoucke & Vandevoorde, 2007).

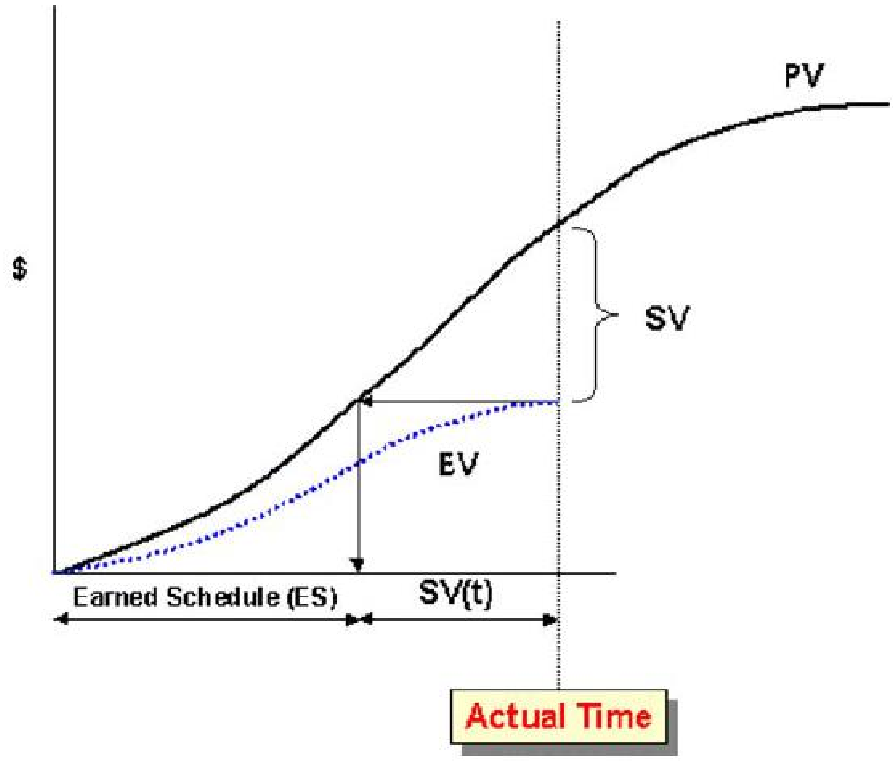

Figure 6 - Earned Schedule concept.
(Source: Vandevoorde and Vanhoucke, 2005)

1.4. Project Forecasting: Estimate at Completion

The information recorded during the monitoring activities are used to delineate project forecasts in terms of Time Estimate at Completion ($TEAC$) and Cost Estimate at Completion ($CEAC$) (De Andrade et al., 2019).

Forecasting cost and duration at completion are Earned Value Management methodologies used with the aim of supporting project managers and PMOs in decision making processes belonging to their ongoing activities (Fleming and Koppelman, 2006). The framework provides diverse techniques to compute the values of $TEAC$ and $CEAC$ by index-based and regression-based computations (Christensen et al., 1995).

Since the objective of the dissertation mainly deepens in the study of cost estimates, in following paragraphs a comprehensive review of $CEAC$ approaches will be provided, whereas, in term of $TEAC$, only the most important index metric formula will be briefly mentioned for the sake of completeness.

1.4.1. Cost and time Estimate at Completion: the index-based review

This section provides for the mostly used index-based formulas coming from various literature, project management textbooks, as well as PMI's Body of Knowledge.

- Original estimate approach:
  The assumption is that the future cost is independent from the past project performance at the time of analysis. The formula to calculate it is:

$$CEAC = ACWP + (BAC - BCWP) = BAC - (BCWP - ACWP) = BAC - CV$$

As it can be noticed, the computation simply implies to subtract the Cost Variance form the initial budget. The significance of this approach lies in its assumption that the trend observed until the project's completion aligns with the BAC, leading to an optimistic outlook by assuming that cost overruns are confined to past occurrences and will not arise in the future.

- Revise estimate approach:
  In order to account for past performance, the formula above is corrected by the CPI index:

$$CEAC = ACWP + (BAC - BCWP) / CI = BAC / CPI$$

  The calculation states to divide the BAC by the CPI which is considered by many to be the best indicator to predict future cost outcomes (Anbari, 2003). If it is greater than one, meaning cost underrun, the $CEAC$ will be less than the BAC, the opposite will happen with a value lower than one. Notwithstanding, the approach assumes that there will be no changes in term of productivity in the future periods.

- Pessimistic approach:
  This method involves both cost deviation and schedule progress. The computation is:

$$CEAC = BAC / (SPI * CPI)$$

  As it is shown, the initial BAC is divided simultaneously by the SPI and the CPI. When both are greater than one the EAC is going to be lower than the initial budget, on the contrary it will be greater when the indexes are lower than one. In case $SPI\ and\ CPI$ have opposite tendency, the effects will compensate each other. The multiplication of the two indexes is called Critical Ratio (CR). Anbari (2003) points out that the CR has the power to depict the complete project performance overview, in turn the pessimistic $CEAC$ computation is agreed to be more realistic. In addition, it is important to notice that the SPI in monetary term can be replaced by the $SPI(t)$ determined by the ES analysis.

- Alternative Pessimistic Approach:
  The performance indexes in the above formula might be combined using a weighted sum (Blythe, 1982). The composite weights are 0,8 for the CPI and 0,2 for the SPI (both monetary and time Schedule index can be used). The formula will be:

$$CEAC = \frac{BAC}{0{,}8 * CPI + 0{,}2 * SPI}$$

  Initially the weights were not fixed. Initially, they were determined by the contribution of the $CV \ and \ SV$ to their total (Lollar, 1980). Further developments suggested to assign values of w_1 and w_2 by various combinations from which the project manager was entitled to choose the best one depending on the project type (Parker, 1980). The subjection to the analysis judgment was overtaken when it has been demonstrated that, using different weights combination in different analyzed dataset, the 0,8 and 0,2 turned out to be the most accurate (Blythe, 1982; Wallender, 1986).

In the context of time at completion estimation ($TEAC$) two formulas are proposed. As it will be noticed, they are based on the actual time spent for the part of already completed work plus the time missing for the remaining activities to be accomplished.

- Original estimate approach:
  The considerations are similar the cost's ones. Time overruns, if occurred, are issues recorded in the past which are not going to affect future evolution. This is the reason why the original approach is also denoted as an optimistic one. The computation is:

$$TEAC = AT + (BAC - BCWP) * (PD - AT) / (BAC - BCWS)$$

  where PD stands for the initial Planned Duration and AT is the time now.

- Revise estimate approach:
  Analogously to the $CEAC$ revised, whether no changes will be registered in the future performance, at least the past progress are integrated thanks to the addition of the SPI or $SPI(t)$.

$$TEAC = AT + (BAC - BCWP) * (PD - AT) / ((BAC - BCWS) * SI)) = PD/SPI$$

As usual, in the case in which $SPI\ or\ SPI(t)$ are less than one, the project is behind the schedule, thus the elapsed at completion will be longer than the PD.

The limitations of these formulas are many. Firstly, the index-based methods completely rely on historical data, in fact only performance indexes are assumed to adjust the budget (Fleming and Koppelman, 2006). Secondly, they compute unreliable forecast outputs during early stages due to the presence of few EVA data at disposal (Zwikael et al., 2000) and are very dependent on the project's nature (Lipke and Walt, 2004). Thirdly, the EAC formulas do not involve physical dynamics such as resource arrangement and impact of indirect costs (Fleming et al., 1997). Lastly, the index-based assumes cumulative project progress to be described by a linear non-S-shaped curves. This means that the last measured performance is not going to change till the end of the work (De Marco, 2014).

As such, studies have been developed to improve these metrics and one of the ways to do that was by incorporating some statistics into forecasting procedures (Christensen et al., 1995). These improved methodologies are presented in the following.

1.4.2. Cost Estimate at Completion: the regression-based review

The regression-based techniques have the objective to enhance $CEAC$ accuracy through fitting curves that better estimate values since project early periods and give the possibility to combine EV and ES performance to explain the variance (Tracy, 2005). The parameters of these kind of models are able to represent the project cost behavior over its whole lifecycle. Here diverse linear and non-linear regression model arising from literature will be outlined.

1.4.2.1. Linear Regression Model

The regression analysis is the procedure that helps understanding the statistical relationship between two variables of which one will be the dependent (Y) and the other the independent one (X). The goal is to estimate the variance of Y given a unit change in X, the so-called slope of the population regression line (Montgomery and Runger, 1999). Furthermore, $\mathcal{E}$ represents the regression error so all other factors not included as variables in the model while measuring for Y.

Hence, the linear regression can be named “simple” if only one regressor is used to explain the predicted variable, or “multiple” if more than one regressor is present in the analysis (Rovezzi, 2002):

- Simple linear regression:
  Only one independent variable is present in the relationship with the dependent variable, with the formula:

$$Y = \beta_0 + \beta_1 X + \mathcal{E}$$

  in which β_0 is the intercept of the regression line, thus the expected value of Y when X is zero. Instead β_1 is the slope of the model so the expected change of Y for a unit change of X.

- Multiple linear regression:
  In this case the linear relationship is between the Y dependent variable and multiple X independent variables. An example can be:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \mathcal{E}$$

in which the intercept of the regression line, denoted as β_0, represents the expected value of the dependent variable Y when the independent variables $X1\ and\ X2$ are both equal to zero. The coefficient β_1 indicates the expected change in the dependent variable Y for a one-unit change in the independent variable $X1$, while keeping the independent variable $X2$ constant. Similarly, the coefficient β_2 represents the expected change in the dependent variable Y for a one-unit change in the independent variable $X2$, while holding the independent variable $X1$ constant.

The “Ordinary Least Square” is the estimator of the unknown beta parameters. It minimizes the average squared difference between the actual values of Y and the prediction based on the estimate line. The linear regression is valid if the Least Square Assumptions are respected which are: linearity between dependent and independent variables, unbiased betas, identical independent distribution of variables, rarity of large outliers, and no multicollinearity implied.

After having determined the regression, model fit on data must be checked to verify the effectiveness of estimated regression model equations (Clogg et al., 1995). The Coefficient of Determination (R^2) is a value from zero to one, expressing the fraction of variance explained by the model relative to the total variance of the observed phenomenon (Montgomery and Runger, 1999). Being equal to one means a perfect fit, while, on the contrary, being equal to 0 means no fit at all, therefore the higher the better. Nevertheless, two important tests are be performed on the model: the $F - test$ and the $t - test$. Here a brief explanation is reported with the aim of further developing on them in the application of linear regressions to the case study under examination:

- $The\ F - test$: used to determine if the model explains a significant portion of the variance in Y and the effect of adding a new predictor in the computation.
- $The\ t - test$: used to assess the statistical significance of a single predictor within the model.

Having gotten the basics behind the linear regression, it is possible to mention examples of literature studies whose analysis are based on implementing the technique with the purpose of improving predictive power and optimization of the Earned Value Management System.

In the context of construction industry, Jaber et al., (2020), among various other authors, applied multiple linear regression to predict the value indicators in tall building projects, meant as a decision-support aid to project managers, contractors, and planners. The models were constructed to better estimate $the\ SPI, the\ CPI\ and\ the\ TCPI$ (To Complete Cost Performance Index) dependent variables with respect to a bunch of regressors such as $BAC, AC, WP, WS, EV\ and\ PD$. Thanks to the adoption of Machine Learning Regression Techniques, it has been possible to demonstrate how good the results were in terms of R^2. Hu et al., (2022) proposed a linear regression model as a control framework to predict productivity for on-site scaffolding activities. The proposed framework combines regression modeling with EVA to track project progress in near real-time.

Looking at the implementation of linear regression models to improve the estimates at completion, several examples can be outlined. Chen (2014) focused on improving the EAC by applying data transformation that allowed better predictions of $EV\ and\ AC$. Hammad et al., (2010) developed multiple regression analysis to forecast cost and duration in construction works highlighting that the project budgeted cost (BAC) and the project planned duration (PD) provide a good basis to compute $TEAC\ and\ CEAC$. They stress that critical path durations and budgets should be modelled following the regression output, thus enhancing the predictive power since the planning phase, so that uncertainty is involved too. Nonetheless, it is important to note that the prediction formulas presented in the paper are specific to public building construction projects in a specific area and is not possible to apply the predict project cost and time in any other type of project. This limitation is crucial when any model is built based on historical data or already existing datasets like the 113 public projects used in their study.

Another interesting contribution has been given by Kose et al., (2022) in their study on the analysis of monitoring practices to complete projects on time and budget. Linear probability models applied to real multiple project data were implemented to understand the relationship between time and cost at completion with the regularity of tracking monitoring activities. The paper's empirical findings indicate that more regularly tracked projects are less likely to experience delays, instead no positive relationship was found to decrease cost overruns. These findings are particularly significant given the growing prevalence of organizational structures involving managers to overseeing multiple projects at the same time and the heightened embedded uncertainty in the environment for monitoring activities.

Multiple linear regression model for improved project cost forecasting

Finally, the "Multiple linear regression model for improved project cost forecasting" by Ottaviani and De Marco (2022) is described. The work had the objective to increase the accuracy and minimize the error variance of the $CEAC$ compared to an index-based standard formula trough a linear regression-based model. The predictive model was developed with the idea of giving clear understating of the relationships between the variables used. The research profits by a dataset of 29 real projects available in literature. The calculation of the linear model in constructed on a three-step statistical analysis. Initially, the selection of the regressors was performed, followed by the verification of lack of correlation between them. Lastly, an examination of the model's properties was conducted. The fitted model is represented by the formula:

$$r\widehat{EAC} = \beta_0 fEAC + \beta_1 CI - \beta_2 WP + \varepsilon$$

where CI is the Cost Performance Index, WP the Work Performed and the $fEAC$ is the forecasted to be adjusted that was embedded in the regression to solve problems related to underfitting. It is expressed by:

$$fEAC = \frac{[AC + (1 - WP)/CI]}{BAC}$$

In relation to the CI, it can be said that not only plays a role in predicting the remaining costs, as indicated by the $fEAC$ formula, but also influences the forecasted total project costs upon completion. Concerning WP, it represents the percentage of work already completed. The negative sign associated with it signifies that both $fEAC\ and\ CI$ contributions to the output decrease as the project approaches its completion stage.

The parameters estimate results describe the fitted model as:

$$r\widehat{EAC} = .70612 fEAC + .45998 CPI - 0.07931 WP$$

The model outperformed the index based EAC method in terms of accuracy and variance. It showed a notable improvement, particularly in Standard Deviation, highlighting the need to enhance the simple EAC computation to capture the evolving correlation among EVM variables. Ottaviani stresses also that additional EVM variables are also necessary to account for trends in cost and time performance indexes.

In conclusion, it can be said that linear regression models are often used due to their easiness and vast utilization across many sectors and organizations, however more complex and sophisticated frameworks and algorithms might be required with the aim of even further improving forecasts and their accuracy. A brief review will be reported in the following part.

1.4.2.2. Non-Linear Regression Model

Nonlinear models have the objective to deeply investigate the S-shape curve that the cumulative values of $PV, EV \; and \; AC$ represent by applying regression analysis. They have capabilities to fit the real cost expenditure behavior of projects.

Nonlinear models rely on modifications with respect to the linear formula proposed in the previous paragraph (Stock and Watson, 2010). For instance, the population regression function of the Y can be approximated by a different higher than one polynomial in the Xs. The coefficients here have more difficult interpretations, being the powers of the same independent variable. Moreover, the dependent and independent variables might be transformed by their logarithms changing the meaning of coefficients once again. For simplicity it is briefly explained the situation of a single regressor explaining the variance of a single independent Y:

- Linear-log regression function: the regressor X is in the form of its logarithm. Here a 1% increase in X (0,1 increase in ln(X)) means a $0,01\beta 1$ change in Y.
- Log-linear regression function: the dependent variable Y is in form of a logarithm and X remains as is. Here a unit increase in X leads to a $100\beta 1\%$ change in Y.
- Log-log regression function: both $Y \; and \; X$ are transformed into logarithms. The interpretation is that a 1% change in X leads to a $\beta 1\%$ change in Y, so that $\beta 1$ represents an elasticity.

In these models R^2 still determines the predictive measurement of fit and it helps to accomplish the most accurate formula for forecasting $CEAC$ (or $TEAC$). Both linear and nonlinear regression-based models require computer programs to compute values such as the R^2.

The efforts for this kind of methodology are more than the one already described. Parameters must have a set of initial values and an algorithm explaining the Least Square Approximation (Bates and Watts, 1988). As in the linear case, historical data are needed to be collected. Finally, the observed data points around the S-curve must follow a Gaussian distribution. Given these considerations, nonlinear curve fitting employs the least squares (LS) method to minimize the sum of squared errors between estimated and actual values, aiming to approximate the model parameters.

Many authors and academics have developed models based on nonlinear regression concept with the aim of improving forecasting accuracy [(Busse, 1977); (Weida, 1977); (Watkins, 1982)]. Nonetheless, more recent studies can be cited. Warburton et al., (2017) purposed non-linear methodologies based on the Earned Schedule and duration principles to demonstrate better performance compared to traditional index-based formulas, particularly in the early stages of project development when corrective actions express their most impact in changing the project's outcome. Besides, Chen and Huang (2006) developed regression models to predict the cost and duration of projects for the reconstruction of schools in central Taiwan. Trahan (2009) implemented Gompertz Model to forecast $CEAC$ thanks to a dataset of EVM data belonging to U.S. Airforce acquisition contracts. The analysis showed good fit to forecast the final cost of projects that registered overruns. Many other authors have continued going further with the implementation of statistics-probabilistic methods. An example can be the study conducted by Barraza et al., (2000) that implemented the progress-based stochastic S-curve profile, incorporating cost and time variances, approached from a probabilistic perspective rather than relying on precise values. The application of this method demonstrated its effectiveness in generating more accurate forecasts, especially in projects characterized by high-risk or non-linear labor profiles. Naeini and Heravi (2011) introduced a new forecasting technique known as the "Beta S-curve method" for estimating the EAC using probabilities and Monte Carlo simulation. Cioffi (2005) purposed a parameterized S-curve tool which was derived from a modified logistic differential equation, to effectively manage the cost of a project during its progression with the aim of adjusting conditions and requirements of the project itself. Lipke et al., (2008) improved cost and time forecasting while applying EVM, ESM through statistical predictions and testing methods.

The discussion of $CEAC$ forecasting enhancement can go on consistently with application of relatively novel and modern approaches: Bayesian model averaging techniques (Kim et al., 2011), the Machine Learning based Artificial Neutral Networks (ANN)

(Iranmanesh and Zarezadeh, 2008) and many others. Since the purpose the dissertation is to apply regression predictive models to a Programme Management-based case study, this part will be not deeply developed. Instead, the very interesting contribution made by Narbaev and De Marco (2014) on Growth Model and Earned Schedule-based regression model to improve $CEAC$ forecasting is going to be deeply developed in the following.

Combination of Growth Model and Earned Schedule to Forecast Project Cost at Completion

Narbaev and De Marco (2014) developed a statistical model in which they addressed the improvement of the $CEAC$ involving the schedule progress. They came up with a combined index-regression method that uses the Gompertz growth model (GGM) to embed in the final formula the time factor of the ES analysis. The graphical representation is presented in the below picture.

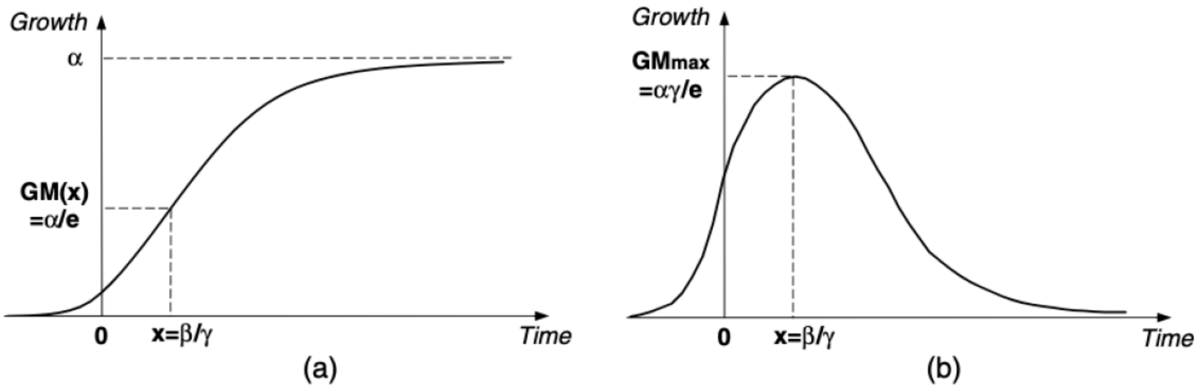

Figure 7 - Gompertz growth model: (a) cumulative growth curve, (b) growth rate curve (Source: Narbaev and De Marco, 2014)

The GGM is explained by the formula:

$$GGM(X) = \alpha e^{[-e^{(\beta-\gamma x)}]}$$

where: x represents the time, α is the model asymptote so the project final cost when t tends to infinity, β the intercept giving the value of the initial budget, and finally γ is a scale factor representing the cost growth rate (GR).

As it can be noticed, the early stage is characterized by slow progress, to be increasing rapidly in the middle stage with inflection registered at one third of the final cost and cumulated value of growth $GGM(x)$ = α/e, at time $x = \beta/\gamma$, when the growth rate reaches the maximum value of $GRmax = \alpha\, \gamma/$e. After that, the growth starts declining as the project comes to its end. The steps to develop the analysis are three and are summarized as follows:

1. Regression analysis to find the growth model's parameters:
   Initially, the time variables are normalized. The PD assumes its maximum value of 1 corresponding to the 100% project time completion, namely the BAC. The cumulated of this unit represent the $GGM\ (x)$ that will be a regressor variable. Furthermore, the AC is normalized from 0 to AT, and the PV to unity from AT to PD. The response variable (y) of the GGM is a combination of $AC\ and\ PV$, thus at each GGM time point (x) corresponds a cost value (y). Finally, $\alpha, \beta, and\ \gamma$ best fit values are determined by performing a nonlinear regression.
2. Estimate at Completion formula:
   The $CEAC$ formula is a combination of the GGM model and index-based methodology, represented by:

   $$EAC = AC(x) + [GGM(1.00) - GGM(x)] * BAC$$

   where: $GGM(1.00)$ is the value when $x = 1.00$ meaning 100% project time complete tending to is α-asymptote, GGM(x) is the value of the model at its AT, consequently their difference as the part of BAC necessary to complete.
3. ES integration:
   In this step the authors want to integrate the schedule progress in the formula:

   $$EAC = AC(x) + [GGM(CF(x)) - GGM(x)] * BAC$$

where: the $GGM(1.00)$ is replaced by $GGM(CF(x))$ that involves $CF(x)$, the so-called Completion Factor. It indicates the forecasted time completion yielded to unity, the reciprocal to the $SPI(t)$. With this regard, if the ES is progressing at the correct pace, the final cost will enhance, on the contrary they would increase. In terms of CF, if equal to 1 the project duration is in line with the planned one, when instead its value is less than one the work is ahead of schedule, when greater than this threshold represents a situation of work lugging behind of schedule. In this way the schedule becomes a cost performance factor, thus the fact of being on time or not influences the $CEAC$.

Having determined the steps to be followed, the model accuracy and precision is checked. The Percentage Error (PE), and the $\text{Mean Absolute Percentage Error}$ ($MAPE$) have been used to assess the former during different project phases, especially early and middle stages. The standard deviation is applied to verify the latter.

To this end, the GGM Both with and without the CF have been compared between three other nonlinear regression models (Logistic, Bass, and Weibull) and a $CEAC$ index-based formula by using a dataset of construction projects. By comparing the $CEAC$ errors of each method, the adjusted CF Factor Gompertz model showed the best fitting performance and the most accuracy in all the project stages.

The academics stress how the purposed model might be adopted in diverse project types and in different progress time stages having tried to apply it to different project portfolios during their analysis. The methodology is one of the few that incorporated an index-based approach with a regression based one. Moreover, the model can improve the $CEAC$ calculation thanks to the presence of the schedule impact affecting the cost trend and can be used for even small sized projects due to the nonlinear more precise properties, in comparison to the index-based that, in this regard, show more predictive failure. To conclude, the authors suggest that future research developments might be focused on transforming the GM technique as artificial intelligence-based one such as ANN, fuzzy logic models and similar, as well as providing a software tool with the aim of making easier and more automated the related computations especially adaptable in construction field.

1.4.2.3. Conclusive remarks

While it is true that linear estimates are often recommended in professional standards and software packages, it is important to understand the reasons behind this recommendation and the context in which it applies. Linear regression models have been widely used and extensively studied, making them well-established and understood by practitioners. They have many advantages, including simplicity, interpretability, and ease of implementation.

Nonlinear regression methods, on the other hand, can be more complex and computationally intensive. They require specifying functional forms and parameters that may not be as straightforward as in linear ones. Additionally, nonlinear models may have multiple local optima, making parameter estimation more challenging and potentially leading to unreliable results if not properly handled.

Moreover, the additional precision gained from nonlinear regression methods may not always be substantial or practically significant. In many cases, linear models can provide a reasonable approximation of the relationship between variables and yield satisfactory results. Therefore, the trade-off between the increased complexity of nonlinear models and the potential gain in precision needs to be carefully considered.

However, it is important to note that there are situations where nonlinear regression methods are indispensable. When the relationship between variables is inherently nonlinear or when linear models fail to capture important features of the data, nonlinear regression can be essential for obtaining accurate and meaningful results. In such cases, it is crucial to apply appropriate techniques and tools specifically designed for handling these kinds of statistical problems.

Overall, the recommendation to use linear estimates in professional standards and software packages is based on a balance between practicality, interpretability, and the typically sufficient precision provided. It is essential to assess the specific requirements of each analysis and consider the potential benefits and drawbacks of nonlinear regression methods to make an informed decision.

In the context of a programme management, there is still the need to try to emphasize further and further statistical predictive models relatively easy to apply, in order to improve Cost Estimate at completion (or more generally Estimate at Completion) for either the overall or single programme components. Here are presented some explanation of the literature gap that justifies the research:

- Lack of emphasis on predictive modeling in the company context: monitoring and controlling activities are usually based on traditional methods and techniques without adequately exploring the potential benefits of statistical predictive models. There is the need to find a good trade-off between accuracy, variance, and difficulty in application.

- Insufficient exploration of data-driven approaches out of the construction field: usually the databases used to validate the regression approaches come from construction projects, there is the necessity to create new predictive models applied in different sectors.
- Need for practical implementation guidance: while theoretical frameworks and models might exist in the literature, there may be a lack of practical guidance on how to implement statistical predictive models effectively within the context of Programme Management. This gap highlights the necessity to bridge the distance between theoretical concept and practical application, providing actionable insights for professionals in the field.
- Neglected potential of statistical predictive models to enhance decision-making: effective Programme Management Monitoring and Controlling require accurate and timely information for decision-making. The literature gap indicates a lack of research that explores how statistical predictive models can assist decision-makers in making informed choices based on reliable EAC estimates. Addressing this gap would provide valuable insights into how predictive modeling can enhance decision-making processes within Programme Management.

By addressing these gaps, the research generally seeks to contribute to the field by investigating the benefits of predictive modeling, improving EAC estimation methodologies, enhancing decision-making processes, and providing practical implementation guidelines.

CHAPTER 2. METHODOLOGY

2.1. Case study Analysis

The study investigates the associations of Cost Estimate at Completion with project performance indicators in the context of an established company programme. The case study research has been chosen because it represents an overall methodological approach thanks to which it is possible to pursue our empirical investigation. Many academics said that this is a very fruitful approach for developing a rich understanding of a complex phenomenon (Eisenhardt and Graebner, 2007). When a case-based study is implemented in the research work, the organization processes is easier to describe and understand too. A deep examination of the reality context and the detection of research variables is allowed (Chiesa *et al.*, 2007). In the following a list of criteria necessary to consider when a case study-based approach is in place are reported:

- Representativeness: the chosen case should respond either to the research purpose and the phenomenon of inquiry.
- Availability of quantity and quality of data to collect in order to have significant information/knowledge building.

The real programme taken into consideration for the purpose of the analysis comes from the IT department of a well-known multinational consulting company in the sector of financial services. More specifically, the business unit practice is the one of front-end Software Testing. The Software Testing is a process carried out to evaluate and assess the quality, functionality, and performance of a software application or system. It involves executing the software with the intention of identifying defects, bugs, or errors to ensure that it meets the specified requirements and functions as expected. It encompasses various activities such as planning, designing test cases, executing tests, and analyzing the results. It aims to uncover any issues that may exist within the software, ensuring that it is reliable, robust, and capable of delivering the desired outcomes. The primary goals of software testing are the improvement of the software quality, the enhancement of user satisfaction, and the minimization of the risks associated with software failures or malfunctions. The sub-practices of interest in the testing program are the ones of Credit Management and the client for whom to perform the work is a well-established Italian bank. The Credit Management covers operations that can be described as follows:

- Credit Granting -> The process of credit granting to bank’s clients. It encompasses the compilation, arrangement, and insertion of necessary documentation and information to analyze the reliability of the client who asks for the granting. The provision applies under the forms of facility credit, personal loans, leasing, factoring, mortgage, and subsidies to open the credit.

- Credit Perfectioning -> Activities involved: credit guarantor document fulfillments necessary for supporting the credit concession; perfectioning of these warranties in terms of date, information insertion, confirmation receipt and transmission to the perfectioned warranties archive.
- Warranties Management -> Revision, renewal and extinction of the warranties given by the bank to its clients.
- Credit Monitoring -> Controlling activities of credit actors to be able to anticipate issues and to potentially report them to the top management. Correct accounting of the registered anomalies takes place. Credit management in case the debtor is not going to respect his/her obligations.
- Credit Revision -> Activities with the aim of reviewing the lending/mortgage. In particular, the persistence of conditions that had determined the credit concessions to the client have to be reverified and confirmed. The guarantor presence continuity is one of the main.
- Post Granting activities -> Subrogation, rate variations, partial extinctions, management of credit variations during the credit elapsed time.
- Non-performing Credit Operations -> Credits with temporary borrower noncompliance. The aim is to seek the best possible interventions to come back to the normal relation conditions, or, conversely, the arrangement of the necessary documentation for the suffering side.
- Pre-dispute Credit Recovery -> The aim is to manage debtors and their compliances as good as possible thanks to the information coming from the monitoring of their positions. The process involves many steps, from the soft collection until the problematic report.
- Credit Extinction -> Activities with the aim of extinguishing the credit and its relative warranties.

The 'Area Credit Programme' is composed by 10 projects with a total elapsed time starting in June 2022 and finish in July 2023. The total budget at disposal is composed by the aggregated sum of all the projects and the cost of work is represented by the human labor necessary to conduct and complete the testing activities. It is a strong model where each project must contribute to the overall programme objective of optimizing the business cost for improving returns. Each project is held by a Test Manager and his/her team, whereas the centralized authority in charge of overseeing and coordinate operations is the Technical Direction in accordance with the company's Business Managers. Each of the project work type activity is interdependent with the others and the firm must be able to optimize the resource allocation, since there may be the situation in which one employee might be working for more than one embedded project assigned to his/her team.

Each project starts with the contract stipulation between the consulting firm and the Information System Direction (ISD) of the bank. The delivery system for all the 10 projects is a Turnkey. This means that the contractor is in charge of the project design and execution, moreover it might short-term finances the activities during the elapsed. The payment scheme is the so-called “Fixed Price”. This means that a fixed lump sum, usually divided in two tranches, is paid to the company for the total scope of contract determined before the start. Indeed, there is no possibility to claim for costs and schedule deviations, unless change of scope occurs and a very precise re-estimation is required from the Test Manager that has to be validated by the bank. This scheme is chosen to incentive the consulting firm to finish the work as early as possible, since the go-live in these kinds of projects has a well-established date that must be respected. Besides, the contractor has the objective of minimizing the cost to accomplish greater profits, being careful at the quality standards to be respected.

Project Analysis and Planning

The project starts with the delivery of the Functional Analysis (FA) from the ISD to the firm, a document containing the software, website or application detailed characteristics and desired performances that will represents the key indicators of the obtained results. After that, Test Managers, in collaboration with the Service Manager and the PMO, can release an estimation in term of time (elapsed testing activities) and cost (total man-days necessary to carry out the work multiplied by a standard average daily company tariff). Usually, being the bank a consolidated client with whom the firm under examination has been collaborating for years, the estimation technique follows an analogical approach. This method is based on comparing the demanded activities with similar already accomplished projects, thus the following steps must be followed:

1. Understanding the testing environment and its peculiarities.
2. Selecting similar past projects of already released activities for the comparison.
3. Identifying the main differences between the new project and the past ones.
4. Applying calculations based on testing metrics and variables to determine the estimation.
5. Evaluation of eventual contingency to apply to cope with critical situations of time and cost overruns (typically <%5% for low-risk projects, between 5%-10% for medium risk projects, and between 10%-12% for high-risk projects). The contingencies follow a process of total man-days re-parameterization relied upon, also in this case, lesson learnt from past projects.

The most important preliminary activity involved in the estimation phase is the planning. The overall project breakdowns into the required activities with an established start and end date, their priority, and interdependencies. The metrics to determine each activity man-days are:

- Test-book total test cases package
- Rate of design progress (test case to write/day)
- Rate of Data Preparation progress (BT/day) and its difficulty rank
- Rate of execution (test case to execute/day),
- %Retest
- The FTEs (the working days in the project activity elapsed time divided by the man-days required)
- Comparison of the resources' price list (€/day) with the standard agreed estimation tariff

The management staff reflects on the necessary consultants to allocate to the project, taking in consideration skills and knowledge required to accomplish each task and an accurate verification of the total engagement of the selected resources in various ongoing projects within the IT department. In this context, the milestones identification is also fundamental to allow team awareness about release deadlines distributed over the total elapsed time.

To have an overview of the activities that a Test Factory project might involve, a detailed description is provided below.

2.1.1. Software Testing project activities

The projects included in the Area Credit Programme follow the Waterfall methodology. This means that the project phases are strictly sequential, and they cannot overlap (Royce, 1970). Each activity is subject to deliverables to be consigned before the next one starts. In this context it is easy to understand if each task has been successfully completed and potential revision are applicable to the single breakdown component. However, the main disadvantage approaching this structure is the inherent inflexibility, hence there is little to no room for work iterations or changes and for facing unexpected issues once one of the phases is completed. This is the reason why big emphasis is required in the above-described planning phase, since to overcome possible deviations from the initial plan, an optimal estimation and its related contingencies must be as accurate as possible. Figure 8 presents the Waterfall approach applied to software testing main phases.

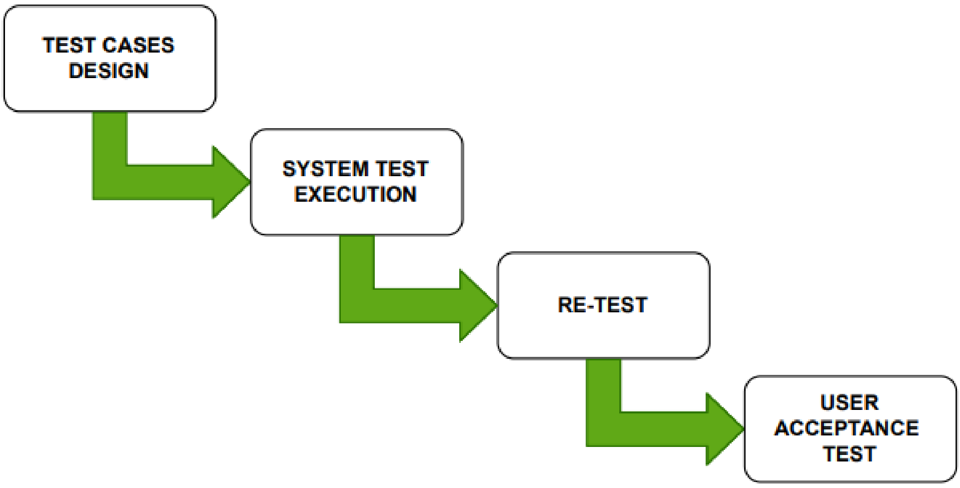

Figure 8 - Main software testing project activities sequentially organized. (Source: author)

The four activities reported above represent the backbone of a common project in the testing field. However, a more detailed and complete description is presented.

- Test Cases Design:
  In the first project phase, the overall test strategy and techniques are outlined, the test environment is identified, and the data requirements collected. The consultants have a fist look to the platforms that need to be tested and alignment with the client are essential at a daily basis. The software functionality is validated, therefore inputs and expected outcomes are clearly stated, positive and negative possible scenarios should be covered to understand the interaction between different components or modules of the system. The test environment, including hardware, software, and network configurations, is prepared to mimic the production environment as closely as possible. This ensures that the testing accurately reflects real-world condition. Based on the client's functional analysis, the consultants write a well define test book that will represent the basis upon which executing the System Test. The test book is the deliverable to be shared with the client in this very moment.

- Data Preparation:

  Data preparation activities involves acquiring, organizing, and configuring relevant test datasets to simulate all possible real-world scenarios. It includes identifying data types, collecting or generating data, cleansing and configuring the set, and managing it for reuse. Effective data preparation ensures accurate testing and helps uncover defects. Assessment of system behavior is performed too.

- Integration Test:

  This phase is present when new lines of codes have been added to an already existing and consolidated architecture in order to check for anomalies embedded in them. Integration testing is a crucial phase in software testing where the interaction and integration between different components are evaluated. Its main objectives include identifying integration issues, verifying interoperability, testing functional flow, and addressing interface problems. By conducting integration testing, software development teams can ensure the reliability and stability of the system when all components are integrated, leading to a high-quality software solution.

- System Test Execution:

  The system test is the most important phase, the core of the testing activities related to the user interface in which most of the effort is required. It represents the longest duration in all the project. Here the goal is to verify the satisfaction of all the requirements listed in the software specification through the systematical executions of all test cases. Testers follow the test scripts and observe the system's response. Any deviations and discrepancies in the behavior of the system from the expected one are identified as reported as defects. Testers document and report these defects using a defect tracking system or a similar tool. They provide detailed information about encountered issues, including steps to reproduce it and any relevant supporting materials. One of the tools used for these purposes is the Application Lifecycle Management (ALM) capable of managing the entire lifecycle of an application, from conception to retirement. The defects here are prioritized to establish a to do list with the aim of fixing them as soon as required. Moreover, the status defect resolution is possible to be tracked. Monitoring activities are fundamental to report progresses and to make sure that the timeline is respected. The count of test executed, passed, failed, and remaining is performed. As new features are added or defects are fixed, regression test might be integrated to verify that no issues or break of existing functionalities take place once the changes have been implemented, so that system's stability is assessed. Overall, the execution validates the software's functionalities, reliability, and performance. It is essential to check if the system is ready for release, it provides valuable insights into the system's quality and readiness for production use.

- Re-Test:
  Right after the system test of a software testing project, the re-testing phase is typically conducted. Re-testing refers to the process of re-executing test cases that previously failed or encountered defects during the main test session, with the purpose of verifying if the reported issues might be sorted out and the desired functionality being restored. Reporting is still crucial in this phase.

- User Acceptance Test Support:
  The UAT focuses on verifying and validating the readiness of the software at the eyes of end users. Being the testing considered from the perspective of the intended final users, the interface friendliness and straightforward utilization must be ensured. These tests are conducted by the so-called "Beta testers", figures not involved in the software development process, with the purpose of uncovering potential usability issues, bugs or gaps in the functionalities not identified in the previous phases. The UAT importance stems from the fact that developers, no matter how well-detailed a requirement may be, need to create a functionality that is initially non-existent and therefore subject to interpretation. Furthermore, certain aspects of the requirements expressed in the contract may only be fully understood by end-users, who can pose challenges for developers during their implementation. It plays a vital role in delivering high quality product and it closes with the sign-off for production use.

- Test Management:
  The activity of overseeing test activities and the management of the team throughout the entire elapsed project time. The primary role of the management staff is to ensure that the testing process is well-planned, efficiently executed and meets the project's quality objectives. In addition, risk assessment, stakeholder communication, mentoring and leadership are considered under the umbrella of managerial responsibilities.

It is important to highlight that the backbone of a software testing projects is represented by the design, execution, re-test and UAT, hence additional activities and tasks described above exist only if specifically requested by the client for each project. With the aim of reporting these differences in the Area Credit Programme, Table 1 is suggested.

Table 1 - Projects of the Programme
(Source: author)

	Test Desing	Data Preparation	Integration Test	System Test Execution	Retest	UAT Support	Test Management
PROJECT 1	✓	✓	✓	✓	✓	✓	✓
PROJECT 2	✓	✓	✓	✓	✓	✓	✓
PROJECT 3	✓	✓	✓	✓	✓	✓	✓
PROJECT 4	✓			✓	✓		✓
PROJECT 5	✓		✓	✓	✓	✓	✓
PROJECT 6	✓	✓	✓	✓	✓	✓	✓
PROJECT 7	✓			✓	✓	✓	✓
PROJECT 8	✓			✓	✓		✓
PROJECT 9	✓	✓	✓	✓	✓	✓	✓
PROJECT 10	✓		✓	✓	✓	✓	✓

Once all projects' activities are completed, the software is ready to be released in production environment respecting the go-live date that usually drops two or three days after the UAT closure.

2.1.2. Teams and Consultant Types

The programme-based case study counts of two teams allocated on the projects, for simplicity the thesis assigns a color as a discriminatory criterion: the first team is the Green Team, the second will be the Blue One. Each of them is in charge of an even number of projects, hence five are assigned to the Green group and five to the Blue group respectively. Table 2 has the purpose of making clear the assignments among the programme.

Table 2- Projects' Assignment
(Source: author)

	Green Team	Blue Team
PROJECT 1	✓	
PROJECT 2	✓	
PROJECT 3		✓
PROJECT 4		✓
PROJECT 5	✓	
PROJECT 6	✓	
PROJECT 7		✓
PROJECT 8		✓
PROJECT 9		✓
PROJECT 10	✓	

The professional figures working on the projects are diverse, each of whom plays an important role in the team and consistently contribute to accomplish projects' objectives. The allocated resources are reported in the following list.

Service Manager

The Service Manager deals with planning, designing, and managing the IT services of the firm. He/she heavily contributes to define the services offered by the company to satisfy the business and especially the client needs in term of digital transformation. The main duties can be summarized in:

- Managing and defining Service Level Agreements (SLAs), Key Performance Indicators (KPIs), and Operational Level Agreements (OLAs)
- Enforcing and negotiating contracts with customers belonging to various business context
- Coordinating the team responsible for recording and fulfilling SLAs
- Monitoring the company's IT system and ensuring optimal performance
- Reviewing all IT activities within the company and directing the staff responsible for maintaining and updating them
- Ensuring that the delivered services meet the interests of the entire involved stakeholders.

- Creating and maintaining customer relationships, including providing support services
- Incorporating the most up-to-date IT Service Management (ITSM) techniques into the workflow
- Developing service improvement and problem management plans

The Service Manager is a figure delineated by the Technical Direction representing the head of the Area Credit Programme. He/she is supposed to be the first and most important interface with the client, validate the estimations provided by test managers and her/his allocation is distributed among the various projects. It is important to say that being a key actor of the Technical Division, the Service Manager is involved in the management of diverse programme and portfolios within the company, thus is not solely working for the programme analyzed in this study.

Test Manager

Each team must entitle a Test Manager for its coordination and management. In the Area Credit Programme under examination, two are the consultants covering this professional figure: the Test Manager of the Green Team and the one head of the Blue Team. Their goal is to manage the overall process and ensure that the software or the system meets the required quality standards and fulfills the intended functionality. As anticipated above, they closely collaborate with the client references and they are at the forefront in the production of project initial estimations, together with the Service Manager and the PMO. The main responsibilities can be reported as follows:

- Test planning and strategy from the study of the Function Analysis until the go-live date. They analyze project requirements, define testing objectives, and determine the scope of testing. They establish test approach, including test levels, types, and techniques to be used. He/she outlines resource allocation, timelines, and dependencies.
- Overseeing and managing the team of testers assigned to projects of his/her cluster, training and guiding them towards the test cases design and execution.
- Monitoring the progresses of the testing activities and documenting outcomes and results. They also participate in defect tracking activities, issues, and risks through specific reports production.
- Collaborating and communicating with developers, test analyst, PMO, and product owners to understand project requirements, clarifying testing goals, and resolve issues or conflicts. He/she is responsible for aligning all the stakeholders involved during the various phases and releases.

- Making sure that the test environments work properly, and that tools and infrastructure are available for testing activities such as hardware, software, and network configuration.
- Improvement of the test process identifying opportunities to enhance the efficiency and effectiveness of testing activities. They may introduce new testing methodologies, tools, or best practices to improve the quality of the overall service.

Test managers represent a key role in IT infrastructures, indispensable for pursuing the program's objectives. In term of allocation, they distribute their working hours among the projects followed by their team.

Test Analyst

Test Analysts work with the management side by side, representing an interface between the latter and the software testers. Their main duties are:

- Planning and Design test scenarios, writing test books and sharing test cases with the testers. They analyze functional specifications and identify areas that require testing, considering both functional and non-functional aspects.
- Test cases execution performing various types of techniques, such as functional testing, regression testing, integration testing, and performance testing, depending on the project requirements.
- Identification and reporting of defects or issues found during the execution. They conduct analysis and investigation to determine root causes of encountered defects. They document and report defects using a bug tracking system, providing clear and detailed information for developers to understand and resolve the issues.
- Creating and maintaining test documentation, including plans, cases, and scripts. They ensure that the test documentation is accurate, up to date, and easily understandable by the team and stakeholders. This documentation serves as a reference for future testing efforts and helps maintain consistency in testing practices.
- Set up and configuration of test environments. They may install and configure software, databases, and other components required.
- Handling of test data management system. It might be also possible to implement data masking techniques to protect sensitive data during testing.
- Handling communication flow regarding testing progress, issues, and risks, ensuring effective coordination and timely resolution of problems. They may participate in meetings to provide for status updates, thus contributing to decision-making processes within the firm.

- Application of best practices designed by the company’s certification body. Hence, active participation in training programs and professional development opportunities is required with the aim of enhancing their testing expertise.

Test analysts can be cross in various team projects under the umbrella of their test manager, however very often they are dedicated to the completion of a single release and only successively they may be assigned to a new project.

Software tester

The Software tester is usually a junior or middle figure within the IT company department. He/she performs specific tasks to test software and applications. The main duties are:

- Identifying software requirements and characteristics
- Participating in designing test plans to be executed
- Executing all assigned tests
- Documenting the procedures necessary for identifying errors and malfunctions
- Preparing reports about obtained results
- Collaborating in debugging and error fixing activities

As for the test analyst, they can be cross figures so that, up to the level of project complexity held by the team, it can be possible to allocate them on more than one activity. It is always the case that this happens.

PMO

An IT PMO is responsible for overseeing and managing IT projects. The primary role of an IT PMO is to provide governance, support, and guidance for project management activities, ensuring that projects are delivered successfully, on time, and within the budget. Here are some key responsibilities and functions:

- Establishes and enforces project governance standards and processes. This includes defining project management methodologies, best practices, and project management frameworks aligned with the organization's goals and objectives.

- Manages the project programme/portfolio, which involves assessing, prioritizing, and selecting projects based on strategic alignment, resource availability, and other criteria. They provide oversight and visibility into the portfolio, ensuring that projects are in line with business priorities and that resources are appropriately allocated.

- Oversees and supports risk management activities within projects. They facilitate risk identification, assessment, and mitigation strategies. They make sure that risks are reported and monitored, and that appropriate risk response plans are in place.
- Facilitates effective stakeholder management and communication throughout the project lifecycle. They collaborate with test managers and the Technical Direction to identify and engage stakeholders, develop communication plans, and ensure timely and relevant project updates and reporting.
- Fosters knowledge sharing and learning within the organization. They capture and document project management lessons learned, best practices, and success stories. They facilitate knowledge transfer between project teams and promote continuous improvement in project management capabilities. The office also works for the standardization of processes within the teams.

Overall, an IT PMO plays a crucial role in driving successful project delivery within the organization. The allocation is to be considered cross in all projects embedded in the programme.

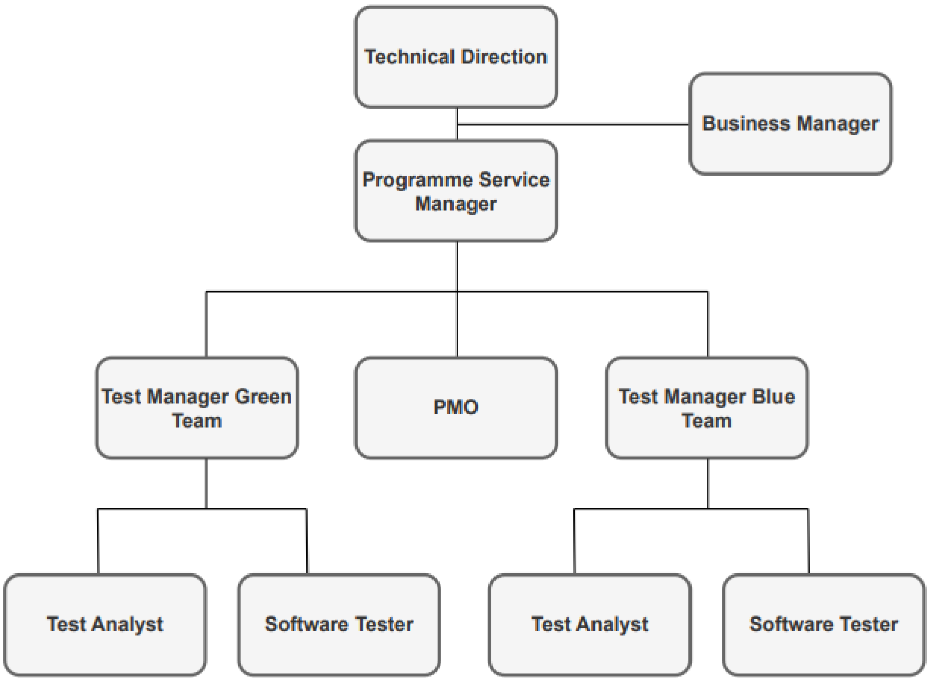

Figure 9 - Resources Breakdown Structure 'Area Credit Programme'
(Source: author)

Figure 9 presents the Resource Breakdown Structure of the Area Credit Programme. Firstly, it can be noticed that the figure of the Business Manager is involved. He/she collaborate with the Technical Direction to make the program reach the expected results and strategic objective in term of profitability and client satisfaction. However, this profile is a part of the commercial structure of the firm mainly focused on seeking new potential clients and contractual agreements and are not directly involved in the progamme management monitoring and controlling. In the context of programme activities his/her role is the delineation of consultants' recruitment and their integration in the teams. It can be also noted that the Test Analyst, even usually being a more skilled and experienced tester than the software testers themselves, does not have, in term of professional profile, a direct control over these figures who always depend directly on the Test Manager. Paradoxically there can be a senior tester that is not necessarily coerced to firstly become a test analyst (due to differences in tasks and activities especially design-driven and data management-driven) when trying to scale up to a managerial position as the one of Test Manager. Here there is not a defined scheme and both testers and analysts develop their own competencies necessary to grow in their careers.

Having understood the organizational structure of the Area Credit Programme, the dissertation moves forward to the variables analysis.

2.2. Dataset Construction

The datasets consist of values of the research variables necessary to conduct the analysis.

The Earned Value and Earned Schedule methodologies have been personally conducted by the candidate during the first working year as a PMO for the company under examination, with the aim of monitoring and controlling the projects of the programme and analyze their final outcomes. Ad-hoc created Excel sheets were used for this purpose.

Initially, a project overview is created. In this first table the main project information are reported: project name, service manager and test manager responsible for, activity description, client name, start and end date, project activities, number of allocated resources, milestones and budget at disposal. Once examined them, the PMO creates the project Gannt Chart, essential to divide the activities and assigned resources' effort during the total elapsed time. The monitoring activities have been performed at a weekly basis. It follows an explanation of how the performance metrics have been computed for each of the project involved.

BAC

To determine the budget at disposal to be monitored in the EV/ES analysis, the first step is the one of subtracting to the total estimated cost the contingency. This amount is put away to cope with possible unexpected risks and overruns, nevertheless it does not have to be necessarily used and, in this case, constitute a pure profit. The formula is:

$$BAC = total\ estimated\ cost * (1 - \%contingency)$$

where %contingency, as explained in the previous paragraph, is a value ranging from 1% to 12% up to the project level of risk depicted by the management staff.

TP

The variable TP represents the time unit at which the project review is carried out. Week 1 will have a value of 1 and so on until the project closure.

BCWS

The scheduling is conducted, as anticipated above, by drawing a Gannt Chart. Each activity has is assigned number of FTEs and the role these FTEs held (Test Manager, Test Analyst and so on). The budget for each project activity is determined by the following formula:

$$BACi = \sum_{j=1}^{m} tariff * n.of consultants * weekworkingdays$$

where $i\ (from\ 1\ to\ n)$ is the activity, $j(from\ 1\ to\ m)$ are the weeks, and the tariff is the daily cost of the consultant recognized at the time of the project estimation to the client. Usually, it is a standard value for any type of resource involved regardless of their professional profile. Nonetheless, there can be a situation in which the tariff applied to test managers 'involvement in terms of man-days on the projects are paid at higher value.

The $BACi$ is also utilized to calculate the weight that each activity has on the total BAC. This percentage is important since it will be used to compute the value of the WP in the next steps. The formula is:

$$WEIGHTi = BACi/BAC$$

At this point, the total budgeted value week-by-week (j) is easily retrievable from the Excel Gantt:

$$BACj = \sum_{i=1}^{n} BACi$$

For each time period TP, the cumulated value of $BACj$, will represent the $BCWSj$ at the time of the project review.

WS

The work schedule in term of percentage can be derived week by week applying:

$$WSj = BCWSj/BAC$$

WP

Each project activity has its own way to calculate the progress. Here the formulas:

$$TestBook\ Design\ \% = \frac{Written\ test\ cases(j)}{tot\ test\ cases}$$

$$Data\ Preparation\% = \frac{Completed\ BT\ (j)}{tot\ BT}$$

$$Integration\ test\% = \frac{Executed\ integrated\ tests\ (j)}{tot\ integrated}$$

$$System\ Test\ Execution\% = passed/(tot\ test\ cases - Not\ applicable)$$

$$Retest\% = \frac{Test\ cases\ retested\ (j)}{tot\ to\ retest}$$

$$Management\% = \frac{Elapsed\ (j)}{total\ project\ Elapsed\ time}$$

$$UAT\ Support\% = \frac{Elapsed\ (j)}{total\ UAT\ Elapsed\ time}$$

in which, Elapsed (j) it is represented by the working days from the start date of the activity to the specific day of the project review (the Friday of the week when the review is carried out), and the total Elapsed time are the working days from the start to the end of the activity.

Having determined the progress for each activity, it is necessary a way to aggregate them to be able to release the total % of project progress at the reference week. The sum product is necessary:

$$WP\%(j) = \sum_{i=1}^{n} (WEIGHTi * activity\%(j))$$

BCWP

Having the project WP at disposal, the computation of the EV at the referral week is straightforward:

$$BCWPj = BAC * WP\%(j)$$

It is also possible to calculate the value for each activity considering the % of progress reported above.

ACWP

The actual costs are calculated taking into account the professional profiles allocated to the project and their relative employment contract type from which their pricelist (€/h) can be detected. With the purpose of keeping secret the corporate sensitive information, fictitious data are used for the actual cost. Hence, the IT consultants' pricelists have been derived from a benchmarking analysis based on the searching of various references and calculation methods present in the web. The web references will follow the bibliography. The actual costs at the reference week j are a sum of each consultant expenditure:

$$ACj = \sum_{i=1}^{n} Pricelist * Consultant\ effective\ working\ hours$$

The cumulated value of ACj at each Time Period (TP) represents the $ACWPj.$

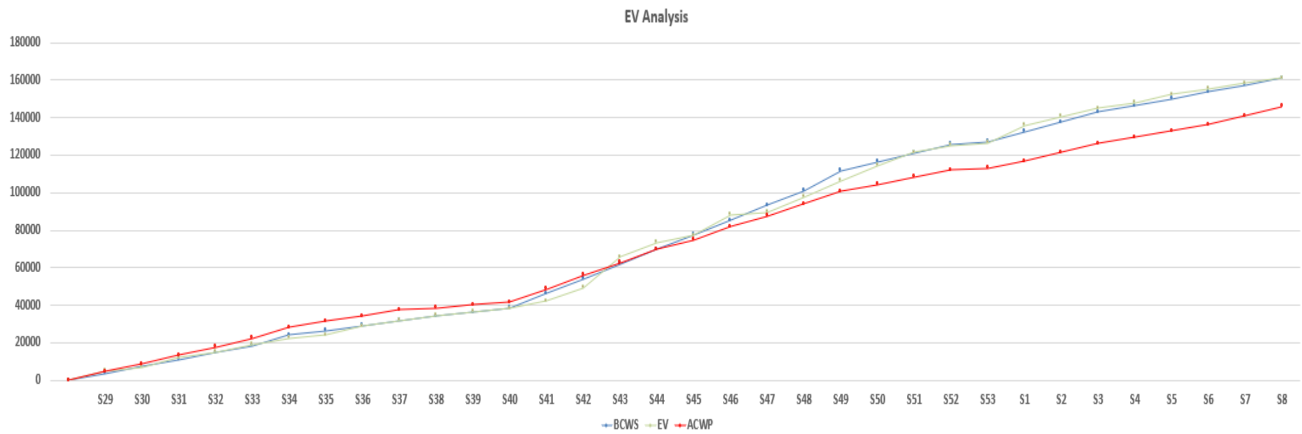

Figure 10 - S-curves example - of the project 3 - completed on schedule and with a cost underrun (Source: author)

DERIVED PERFORMANCE INDEXES

Once the $BCWS, BCWP, and\ the\ ACWP$ are calculated, it is possible to derive the following performance indicators applying the formulae reported in the literature during the project weeks:

- Earned Schedule (ES)
- Cost Performance Index (CPI)

- Schedule Performance Index (SPI)
- Schedule Performance Index in time value ($SPIt$)
- Cost Variance (CV)
- Schedule Variance (SV)
- Resource Flow Index (RFI)
- Resource Variance (RV)

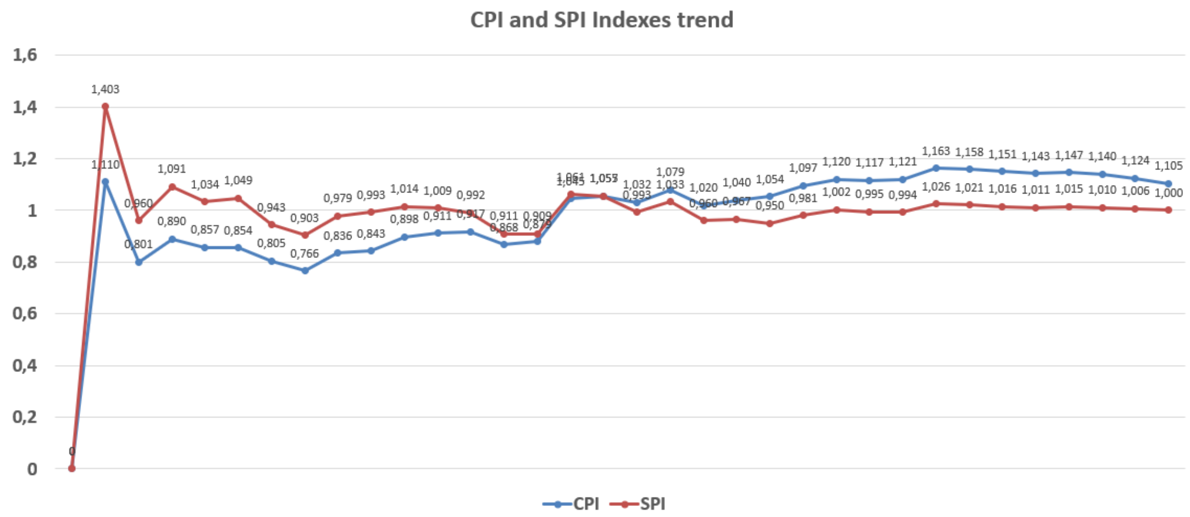

Figure 11 - CPI and SPI trend example – project 3-
(Source: author)

All described variables will be part of the database that is going to be used to run statistical predictive models. At this point, the weekly values have been successively scaled with the aim of comparing them on the same scale and improving the model tailoring. The values to insert into the model will be:

$$BACn = \frac{BAC}{BAC} = 1$$

$$TPn = TP/PD$$

$$ACn = ACWP/BAC$$

$$ESn = \frac{ES}{PD}$$

Being already in the form of indexes, the $CPI, SPI, SPIt, and\ RFI$ stay unchanged regardless of the scaling process. Looking at the $BCWS\ and\ BCWP$ they are exchanged with their scaled versions, $WS\ and\ WP$ respectively.

Likewise, it is possible to derive:

$$CVn = WP - ACn$$

$$SVn = WP - WS$$

$$RVn = WS - ACn$$

To determine the scaled version of the actual duration and actual cost at moment of roject completion there will be:

$$ADn = AD/PD$$

$$ACn\ (ADn) = CACn = \ Max\ (ACWP)/BAC$$

To conclude the part related to the database description, an overview of the programme outcomes is proposed in the Table 3.

Table 3 - Programme Outcomes (CO = cost overrun; CU = cost underrun; EF = early finish; LF = late finish; OB = on-budget; and OS = on schedule)
(Source: author)

	PD (weeks)	AD (weeks)	ADn	$ACn\ (ADn)$	OUTCOME
PROJECT 1	27	27	1	0,537	CU-OS
PROJECT 2	21	21	1	0,845	CU-OS
PROJECT 3	33	33	1	0,905	CU-OS
PROJECT 4	18	19	1,055	1,111	CO-LF
PROJECT 5	26	29	1,115	1,338	CO-LF
PROJECT 6	15	15	1	0,590	CU-OS
PROJECT 7	26	28	1,076	0,919	CU-LF
PROJECT 8	18	19	1,055	1,409	CO-LF
PROJECT 9	18	21	1,166	1,018	CO-LF
PROJECT 10	27	29	1,074	1,198	CO-LF

2.3. Correlation Analysis

Forecasting project cost at completion is a key factor to assure the project success. The PMO group wants to find a simple applicable approach to better estimate the $CEAC$ that might help the company to monitoring the value throughout the whole project life. More specifically, the Office has the purpose of utilizing the already calculated EV and ES project performance parameters to create models that might produce a more accurate and precise estimation of the $CEAC$. The first model is based on the total dataset available, the second and third model are based instead on two of its sub-sets, thus there will be:

- FULL DATASET: predictive model estimation applied to the overall Area Credit Programme.
- GREEN TEAM DATESET: predictive model estimation applied to the Green Team projects.
- BLUE TEAM DATESET: predictive model estimation applied to the Blue Team projects.

In this way a benchmarking analysis is possible to perform with the aim of discovering which variables affect the most the three scenarios, pointing out the significant differences between the teams, and how they vary with respect to the full data collection.

The first step that helps to strengthen the process of $CEAC$ estimation is the correlation analysis between the $CACn$ and the EVM project descriptors reported in the previous paragraph. The model to keep in mind is:

$$CACn = f(TPn, CPI, SPI, RFI, WS, WP, ACn, ESn, CVn, SVn, RVn)$$

In order not to complicate even further the calculation, only the $SPI(€)$ has been counted as a variable excluding instead the $SPIt$, since the former is the most widely used during the PMO's monitoring activities.

HYPOTESHIS

For the correlations, SAS® Studio environment has been used. The outcomes are going to be compared with the initial hypothesis made up by the PMO in order to verify the initial expectations coming from the company's point of view. The hypothesis are presented as follows:

1. TPn -> The PMO does not know how the normalized time period might affect the $CACn$, in reality the idea is that there should not be any possible correlation. It can be thought that, the more the projects progress the more the final costs, but this is not necessarily true since from the EVM for some periods in some projects the $CACn$ tends to diminish as the time goes by. Upon what explained, no correlation with the dependent variable is expected.
2. WS -> The PMO knows that the normalized version of the $BCWS$ grows week after week until reaching the 100% at the time the activities are planned to be ended. The fact that WS cumulates alongside the project progress does not mean a simultaneous increase of $CACn$. The Office expects no correlation between the two.
3. WP -> The same as for WS. No correlation is hypothesized.
4. ACn -> Being the normalized version of $ACWP$ the company expects positive relationship between this feature and $CACn$, being the latter the expression of the AC once the project is at completion.
5. CPI -> In the index-based methods coming from literature, the CPI is always negatively correlated with the final costs. The more the CPI is greater than one, the better the cost performance. In turn the $CACn$ is expected to be lower. The correlation should be negative.
6. SPI -> The same as for the CPI. Negative correlation is assumed.
7. CVn, SVn -> Also, in term of Cost Variance and Schedule Variance normalized, the more the values are greater than 0, the better the project performances, meaning that the project is spending less than the budgeted and is ahead of time. The relations with the $CACn$, for the PMO, are thought to be negative.
8. RFI, RVn -> The more the RFI is greater than 1 and RVn greater than 0, the better are the performance. In turn, $CACn$ is supposed to be negatively correlated with these two metrics.
9. ESn -> being the EV in term of time, the ES normalized should follow the same meaning expressed at point 3, thus no correlation with the final effective project costs is hypothesized.

CORRELATION MATRICES

To correctly interpret the correlation matrix outcome, it is important to know how the correlation coefficient (or Pearson coefficient) works:

- If the correlation coefficient ρ > 0, the two variables are positively correlated. This means that as the value of one variable increases, the value of the other variable also tends to increase.
- If the correlation coefficient ρ = 0, the two variables are uncorrelated.
- If the correlation coefficient ρ < 0, the variables are negatively correlated. This means that as the value of one variable decreases, the value of the other variable tends to increase.

Regarding the correlation importance three cases exists:

- If 0 < |ρ| < 0.3, there is weak correlation.
- If 0.3 < |ρ| < 0.7, there is moderate correlation.
- If |ρ| > 0.7, there is strong correlation.

SAS® Studio environment also provides for the t-test, the one that checks for the null hypothesis:

- If the p-value <5% the null hypothesis is rejected, and the variables are statistically significant correlated (at a confidence level of 95%).
- If the p-value >5% the null hypothesis is accepted, thus the variables are statistically significant uncorrelated (at a confidence level of 95%).

Data polishing was required. From the totality of observations, it was necessary to remove the time periods in which project progress was not registered ($WP = 0$) as well as the weeks in which the project is at completion ($WP = 100\%$). Having done that for each project and having aggregated data to create the dataset columns, 231 total values for each variable were counted in the full database. The matrix is reported in Table 4.

Table 4 - Correlation Analysis Entire Programme
(Source: SAS® Studio)

Pearson Correlation Coefficients, N = 231 Prob > |r| under H0: Rho=0												
	CACn	**TPn**	**WS**	**WP**	**ACn**	**CPI**	**SPI**	**CVn**	**SVn**	**RFI**	**RVn**	**ESn**
CACn	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
TPn	0.05513 0.4043	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
WS	0.03103 0.6389	0.98411 <.0001	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
WP	-0.06338 0.3375	0.97441 <.0001	0.97978 <.0001	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
ACn	0.30333 <.0001	0.93546 <.0001	0.92741 <.0001	0.89309 <.0001	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
CPI	-0.75345 <.0001	0.39460 <.0001	0.41532 <.0001	0.50251 <.0001	0.11838 0.0725	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
SPI	-0.38750 <.0001	0.34156 <.0001	0.30547 <.0001	0.43448 <.0001	0.23894 0.0002	0.63538 <.0001	1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
CVn	-0.79538 <.0001	0.06455 0.3287	0.09360 0.1562	0.21166 0.0012	-0.25065 0.0001	0.82418 <.0001	0.41587 <.0001	1	[redacted]	[redacted]	[redacted]	[redacted]
SVn	-0.45793 <.0001	-0.23423 0.0003	-0.28756 <.0001	-0.09014 0.1721	-0.34122 <.0001	0.33819 <.0001	0.55935 <.0001	0.54732 <.0001	1	[redacted]	[redacted]	[redacted]
RFI	-0.73117 <.0001	0.29642 <.0001	0.34579 <.0001	0.36821 <.0001	0.01682 0.7993	0.88320 <.0001	0.21703 0.0009	0.75580 <.0001	0.04133 0.5320	1	[redacted]	[redacted]
RVn	-0.69966 <.0001	0.20155 0.0021	0.26448 <.0001	0.29927 <.0001	-0.11545 0.0799	0.79771 <.0001	0.19517 0.0029	0.89481 <.0001	0.11611 0.0782	0.87492 <.0001	1	[redacted]
ESn	-0.05443 0.4103	0.97880 <.0001	0.95736 <.0001	0.98429 <.0001	0.88244 <.0001	0.49858 <.0001	0.46462 <.0001	0.20098 0.0021	-0.05370 0.4166	0.34718 <.0001	0.26717 <.0001	1

Table 5 presents the correlation outcomes:

Table 5 - CACn correlation results
(Source: author)

	Correlation with $CACn$
TPn	NO correlation
WS	NO correlation
WP	NO correlation
ACn	Moderate Positive
CPI	Strong Negative
SPI	Moderate Negative
CVn	Strong Negative
SVn	Moderate Negative
RFI	Strong Negative
RVn	Moderate Negative
ESn	No correlation

The variable ACn expresses moderate positive relationship with $CACn$ by a Pearson Coefficient equal to 0,3. Being the cumulated actual cost normalized, this variable can assume value ranging from 0 to $CACn$. It grows over time except for the week where no progress is made, a case the latter happened very rarely. The cost index and variance, respectively the CPI and CVn seem to be much more correlated with the final project expenditure than the time performance indicators SPI and SVn. The first two express both strong negative relationship with the final cost, so that the better the performances the lower the $CACn$, the last ones, on the other hand, exhibit still good correlation response but not as strong as the cost metrics, expressing moderate negative relationships. Yet it is possible to affirm that the higher their values, the lower will be the cost to be borne.

Likewise, the RFI and RVn have registered certain correlation results. An RFI greater than 1 indicates that the effort estimation has been successfully budgeted ex-ante and that the PMO, alongside with the test manager and service manager, have been efficiently allocating project resources at their disposal over the elapsed. The correct allocation, task assignments, balanced workload and optimization of human, time and technological resources means also lower final effective project cost with a strong negative correlation. Similar behavior is displayed by the RVn. Indeed, when the difference $WS - ACn$ grows, more economical efficiency in accounting terms is registered, in turn the $CACn$ tends to decrease. By demonstrating a Pearson coefficient of -0,69, it can be said that there is a strong negative correlation even though, formally, is still to be considered moderate negative. Overall, the behavior can be compared to the RFI's one.

Finally, the variables $TPn, WS, WP, and\ ESn$ show p-value greater than the maximum acceptable threshold. The cost at completion has nothing to do with the time period increments, and with the project planned and effective progress. Surely the implementation of ES Analysis brings on the table some advantages (forecasting project completion dates, better determining time discrepancies, calculating the $SPIt$), however in term of correlation with $CACn$ it does not give any hints.

Besides the final project cost outcomes, other interesting findings may be captured between the EVM indicators:

1. WS, WP, ACn, ESn with TPn -> Their interactions confirm the EVM S-curves evolution.
2. CPI with TPn, WS, WP -> As the projects progress, the CPI shows a moderate positive correlation with the three variables, meaning that it improves over time and over project progresses even if in moderate terms. The same can be said for the SPI
3. SPI and CPI -> They exhibit a moderate positive correlation between each other, when one improves the other follows the same trend.
4. SVn and CVn -> moderate similar behavior, positively correlated.

5. CVn and CPI-> the Pearson Coefficent is equal to 0,82. As it could be expected, they behave in the same manner.
6. SVn with SPI -> moderate similar behavior, positively correlated.
7. RFI and CPI -> strongly affecting each other in a positive manner. When CPI increases, RFI will follow the trend. The same consideration is demonstrated with the CVn, the correlation coefficient is slightly lower still strongly positive.
8. RVn with CPI, CVn -> strongly positive especially with the latter.
9. RVn and RFI -> As it might be expected, very similar behavior with a positive correlation of 0,87 appears.

To conclude, the correlation benchmarking with the Green Team dataset and the Blue Team one containing five projects each is presented. The former counts for 116 total observations, while 115 are for the latter. The outcomes are presented in Table 6.

Table 6 - Correlation analysis benchmarking (Source: author)

	FULL DATASET	**GREEN TEAM**	**BLUE TEAM**
	Correlation	**Correlation**	**Correlation**
TPn	NO correlation	NO correlation	NO correlation
WS	NO correlation	NO correlation	NO correlation
WP	NO correlation	NO correlation	NO correlation
ACn	Moderate Positive	Moderate Positive	NO correlation
CPI	Strong Negative	Strong Negative	Moderate Negative
SPI	Moderate Negative	Moderate Negative	Moderate Negative
CVn	Strong Negative	Strong Negative	Strong Negative
SVn	Moderate Negative	Moderate Negative	Moderate Negative
RFI	Strong Negative	Strong Negative	Moderate Negative
RVn	Moderate Negative	Strong Negative	Moderate Negative
Esn	NO correlation	NO correlation	NO correlation

As it can be noticed, there are no significant differences among the analysis. The only relevant comment might be done about the ACn of the Blue Team presenting a no correlation with the $CACn$, whereas the Green Team sticks with the overall dataset findings. In this case, the PMO's expectation is going to be rejected, since the relation should have been positive if based on company' s believes. The correlation shows a $p - value$ equal to 0,175 so that the null hypothesis cannot be rejected. Therefore, the incidence of the cumulative actual costs on the final effective costs could be questionable, looking at the 5 projects assigned to the Blues. Overall, it can be concluded that the correlation analysis exhibit in the vast majority the same outcomes.

2.4. Evaluation of the Models

Having determined the correlations among variables, linear regressions are employed to determine the predictive models based on the three datasets. The goal is to investigate the association between the dependent variable Cost at Completion and the independent regressors represented by the EVM and ES performance parameters presented in the correlation analysis. This is done to follow the PMO's willingness to establish predictive models able to better estimate final costs in the context of a Software Testing programme. The office needs a model easy to apply during the weekly monitoring and controlling activities without any difficulty in terms of interpretation. For this purpose, linear probability model has been chosen over other ones. The regression will be run by:

$$CACn = f(TPn, CPI, SPI, RFI, WS, WP, ACn, ESn, CVn, SVn, RVn, BACn)$$

As it can be noticed, there is an additional regressor added into the model: the $BACn$. Thus, an additional column will be introduced in the datasets whose observations will be all equal to 1, being the $BACn$ the initial projects' budgets scaled by themselves. This is essentially done for two reasons:

- Scale effect -> The $BACn$ can help to control the model scale effect. It acts as a reference point for estimating all other regression coefficients.
- Intercept interpretation -> In the linear regression, the intercept represents the predicted value of the dependent variable when all regressors are equal to 0. Considering $BACn$ always equal to 1, it represents the intercept on the y-axis when all the project parameters have a 0 value, meaning that the project is not started yet, hence the initial budget figures as the estimated cost at completion.

The procedure follows substantially two steps. Firstly, having implemented a totality of twelve EVM indicators as independent regressors, the problem related to overfitting and multicollinearity must be solved. These issues might be not only present due to the high number of variables itself, but mostly because of their nature of being fundamental and derived quantities provided by the Earned Value Analysis. Having sorted them out, the linear regression analysis will be performed to find the regressors' coefficients.

To overcome the multicollinearity SAS® Studio GLMSELECT procedure was used, thanks to which it is possible to evaluate the impact of each variable that enters the model for determining fitness. The selection criterion was the Least Absolute Shrinkage and Selection Operator (LASSO). It is based on shrinkage regularization of the model parameters and is one of the most used in literature papers. The LASSO does not specifically select the variables, but instead puts some penalties to shrink the regression coefficients towards 0 (if the shrinkage is large enough, it sets some of the coefficients to exactly 0). Its goal is to provide the model with smallest estimated prediction error (Tibshirani, 1996).

$$\tilde{\beta} = arg\ min_{\beta} \sum_{i=1}^{N} (Y_i - (X\beta)_i)^2$$

$$\text{subject to } p(\beta) \leq t$$

$$p(\beta) = \sum_{j=1}^{p} \mid \beta_j \mid$$

The shrinkage and regularization method is presented in its minimization form. It can be noticed how the Residual Sum of Squares (RSS), that is the squared difference between the predicted values of the model and the actual observations, is minimized and subject to a penalty on the coefficients β, expressed by function p that is the sum of the absolute values of the regression coefficients. Moreover, t is the shrinkage parameter. As the latter decreases, the coefficients shrink towards 0. The continuous shrinkage reduces the variance of coefficient esteems and improves the accuracy fit, letting the variables competing for inclusion in the model. The algorithm behind the structure is the LARS algorithm (Efron et al., 2003).

2.4.1. Lasso selection and Multiple Linear Regression procedure

2.4.1.1. Entire Programme dataset

The LASSO has been applied to the full programme dataset to evaluate the fit statistics evolution. Figure 12 gives the coefficients plot, thus showing how the regression coefficients change during the selection process. The x-axis presents the shrinkage parameter t, the y-axis shows the standardized coefficient values for the regressors when t varies. As t decreases, more penalty is imposed, and coefficient estimates move toward 0. To determine the LASSO optimal model, so the one that gives the smallest estimated predication error, the x-axis shrinkage parameter is determined. Being the default one, the indirect estimation method called "Schwarz information criterion" (SBC) has been assessed. SBC mathematical adjusts the RSS by using model complexity and the sample size to decrease the bias due to overfitting in the training data. The smaller the SBC on the LASSO path, the better the fit.

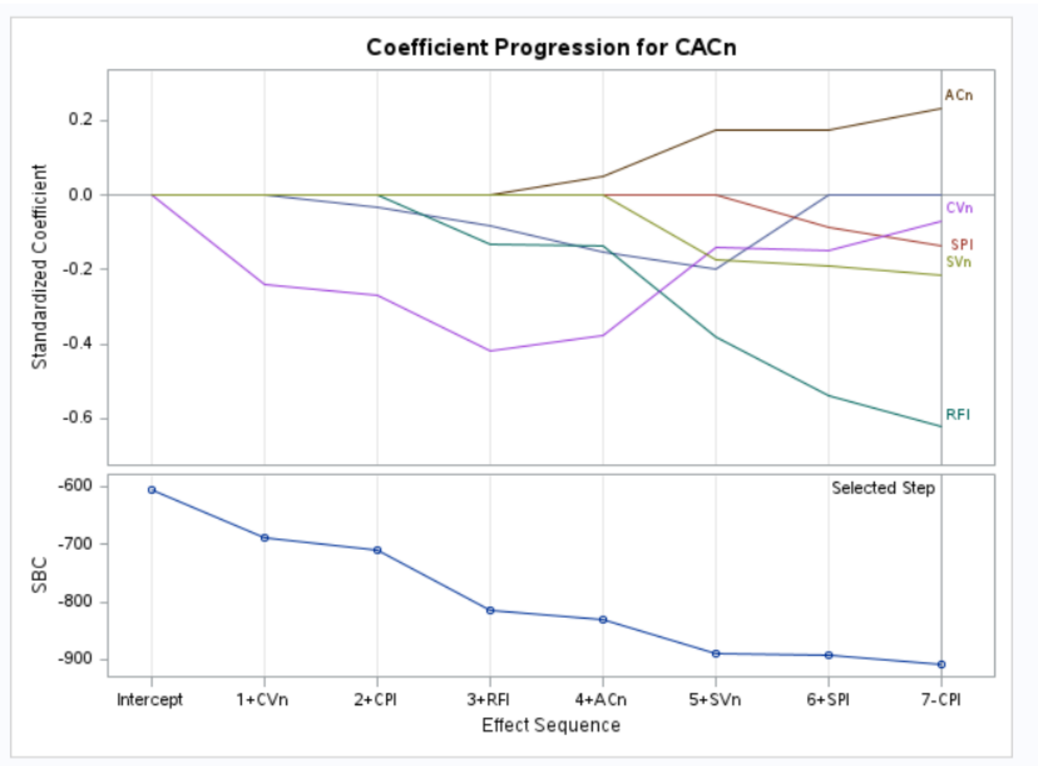

Figure 12 - LASSO solution path at a programme level
(Source: SAS® Studio)

Table 7 shows the SBC value change for each model on the LASSO path until the stop of the selection procedure, preventing other coefficients to enter the model. As observable, the smallest SBC is the one at step seven. The last step removes the CPI definitively.

Table 7 - LASSO steps at a programme level (Source: SAS® Studio)

The GLMSELECT Procedure

LASSO Selection Summary				
Step	Effect Entered	Effect Removed	Number Effects In	SBC
0	Intercept		1	-605.3004
1	CVn		2	-689.7938
2	CPI		3	-708.8031
3	RFI		4	-814.6002
4	ACn		5	-830.8013
5	SVn		6	-890.3796
6	SPI		7	-892.5016
7		CPI	6	-908.5875*
* Optimal Value of Criterion				

Selection stopped at a local minimum of the SBC criterion.

Stop Details				
Candidate For	Effect	Candidate SBC		Compare SBC
Entry	TPn	-903.4312	>	-908.5875

The next graph shows how the Average Square Error has been decreasing by reaching the SBC smallest value, justifying what said above.

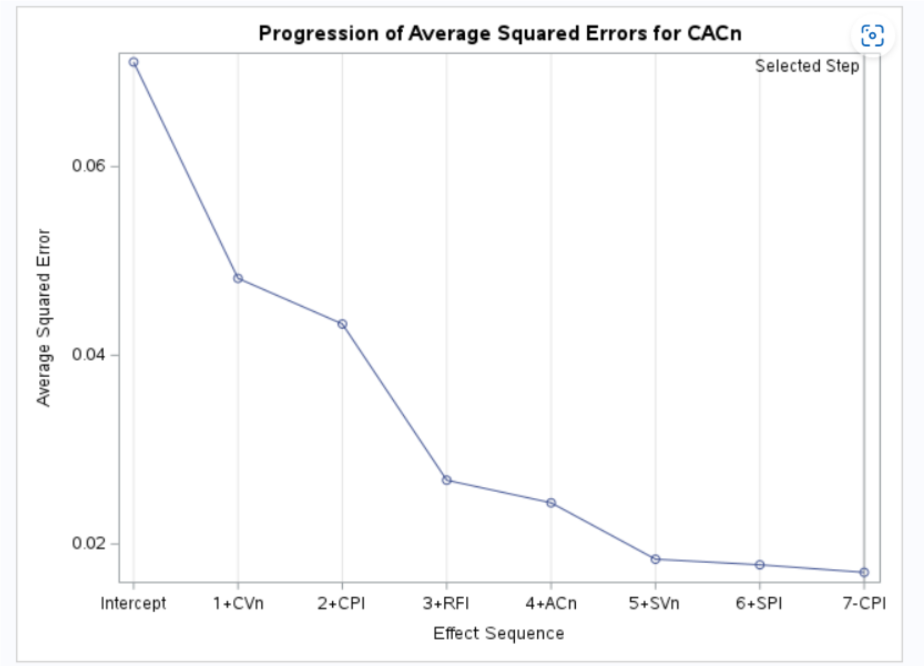

Figure 13 - Average Square Error downward
(Source: SAS® Studio)

The procedure suggests the following variables to explain the variance of $CACn$: SPI, RFI, ACn, CVn, and SVn.

Finally, the SAS® Studio GLM procedure can be applied for performing statistical regression. The first regression ANOVA results show statistical significance, nonetheless, when looking at statistics of the model regressors, CVn expresses its p-value as a value equal to 0,779, thus greater than the 5% statistical threshold to reject the null hypothesis. This is the reason why it is suggested to repeat the linear regression by removing from the GLM model the Cost Variance normalized variable.

FINAL MODEL

The ultimate model to be analyzed is expressed by:

$$CACn = f(SPI, RFI, ACn, SVn)$$

Once repeated the GLM Procedure, the ANOVA results are possible to be commented.

Table 8 - ANOVA results Full Dataset
(Source: SAS® Studio)

The GLM Procedure

Dependent Variable: CACn CACn

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	12.52228333	3.13057083	181.51	<.0001
Error	226	3.89787141	0.01724722		
Corrected Total	230	16.42015474			

R-Square	Coeff Var	Root MSE	CACn Mean
0.762617	13.20525	0.131329	0.994519

To test the overall utility of the model, F-Value and the corresponding $p - value$ are interpreted. Being the former equal to 181,51 and the latter lower than 5%, it can be said that the predictions show a significant linear relationship. Furthermore, reading the R-square value, 76% of the dependent variable variation is explained determining a good fit.

The table 9 will report the estimation of the slope terms for all selected regressors.

Table 9 - Coefficients Estimation Full Dataset
(Source: SAS® Studio)

Parameter	Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	1.801334738	0.07247124	24.86	<.0001	1.658528981	1.944140495
SPI	-0.288313285	0.08407689	-3.43	0.0007	-0.453988154	-0.122638417
RFI	-0.662342765	0.03227636	-20.52	<.0001	-0.725943861	-0.598741668
ACn	0.230317654	0.03530995	6.52	<.0001	0.160738832	0.299896476
SVn	-0.998991368	0.20076853	-4.98	<.0001	-1.394609022	-0.603373714

The $SPI, RFI, ACn, and\ SVn$ appear to be important and useful since the corresponding p-values are all lower than the threshold, rejecting the null hypothesis. For the variables embedded in the final model, the multicollinearity issue is said to be solved considering that, from the correlation analysis, none of the interactions between the independent variables express a strong relationship.

2.4.1.2. Green Team Dataset

The dissertation is aimed at comparing what has been determined from the whole programme predictive analysis with two other statistical models expressed in terms of programme allocated teams, in order to observe what are the main differences and especially determining which variables affect the most the $CACn$ for both the 5 projects scenario of the Green and the 5 projects scenario of the Blue one.

Starting with the Green team, the same step followed for the full dataset are applied. Firstly, the LASSO procedure results are reported, as it can be observed in the coefficients plot of the selection process.

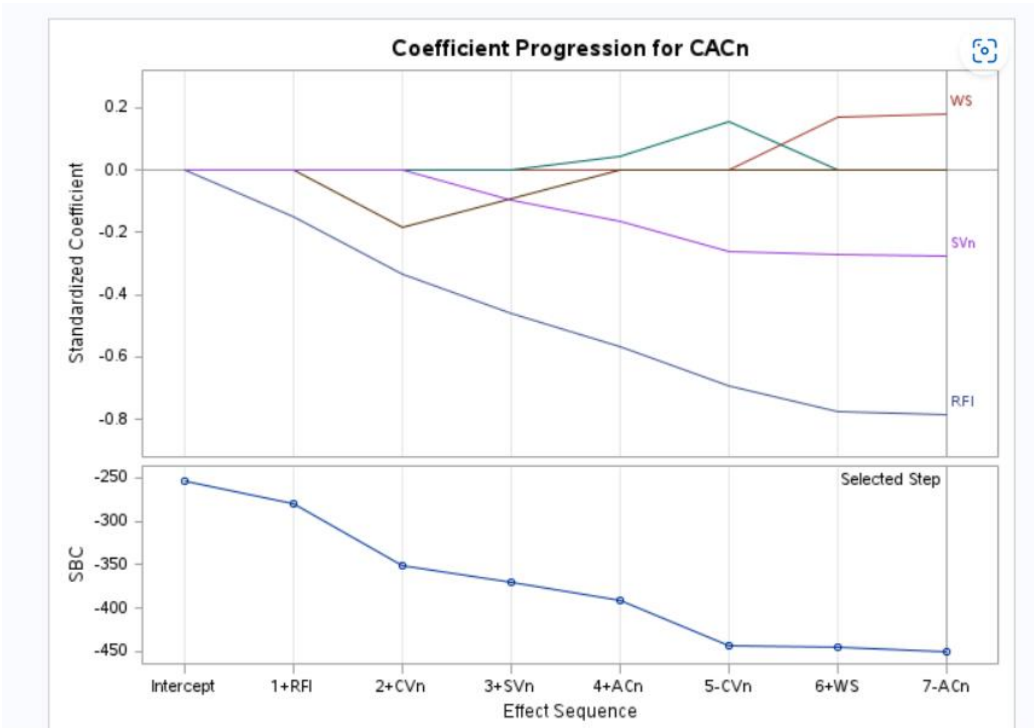

Figure 14 - LASSO solution path Green team's projects (Source: SAS® Studio)

The SBC downwards until the step seven where any other variable is not allowed to enter in the solution. As it can be seen from the table 10, the smallest SBC is equal to -450.285. Particularly, both the variables CVn and ACn are initially involved as effect entered, nevertheless consecutively discarded from the final solution model that minimized the average square errors.

Table 10 - LASSO steps Green Team Dataset (Source: SAS® Studio)

The GLMSELECT Procedure

LASSO Selection Summary				
Step	Effect Entered	Effect Removed	Number Effects In	SBC
0	Intercept		1	-254.4478
1	RFI		2	-279.1711
2	CVn		3	-350.1775
3	SVn		4	-370.6576
4	ACn		5	-390.5960
5		CVn	4	-442.5488
6	WS		5	-444.6163
7		ACn	4	-450.2850*
* Optimal Value of Criterion				

Selection stopped at a local minimum of the SBC criterion.

Stop Details				
Candidate For	Effect	Candidate SBC		Compare SBC
Entry	SPI	-448.0997	>	-450.2850

The procedure suggests the following variables to explain the variance of $CACn$: $RFI, WS, and\ SVn$.

FINAL MODEL

The ultimate model for the Green Team sub-set is:

$$CACn = f(RFI, WS, SVn)$$

The correspond ANOVA table released by the SAS GLM linear regression are reported in the following.

Table 11 - ANOVA results Green Team sub-set
(Source: SAS® Studio)

The GLM Procedure

Dependent Variable: CACn CACn

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	10.42489325	3.47496442	195.33	<.0001
Error	112	1.99246674	0.01778988		
Corrected Total	115	12.41735998			

R-Square	Coeff Var	Root MSE	CACn Mean
0.839542	14.04190	0.133379	0.949862

The results demonstrate a greater overall model utility compared to the programme predicitive model. In fact, the F-statistics are equal to 195,33 in comparison to the previous 181,51. Thus, statistical validity has been confirmed. In term of model fitting, similar considerations can be redacted, being the R-square equal to 84%. The independent variables explain a very big portion of the Cost at Completion.

The next step is to read the provided parameters estimates.

Table 12 - Parameter estimations Green Team model
(Source: SAS® Studio)

Parameter	Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	1.660367881	0.04919611	33.75	<.0001	1.562892088	1.757843675
RFI	-0.786789583	0.03958575	-19.88	<.0001	-0.865223669	-0.708355498
WS	0.226160961	0.04229001	5.35	<.0001	0.142368721	0.309953200
SVn	-1.633672662	0.22815170	-7.16	<.0001	-2.085726010	-1.181619315

The t-statistics and corresponding p-values of the three regressors involved in the model show one by one to be significant in explaining the independent variable. In this case the regression final selected variables coincide with the ones directly selected by the LASSO coefficient shrinkage mechanism. The multicollinearity issue can be confirmed to be solved since the remaining Xs does not show any correlation in the Green Team correlation matrix.

2.4.1.3. Blue Team Dataset

The last sub-set to be analyzed is the Blue Team one. The LASSO mechanism is presented as usual by the regression coefficients change on the solution path. The optimal model which gives the smallest estimated predication error is determined by the smallest shrinkage parameter.

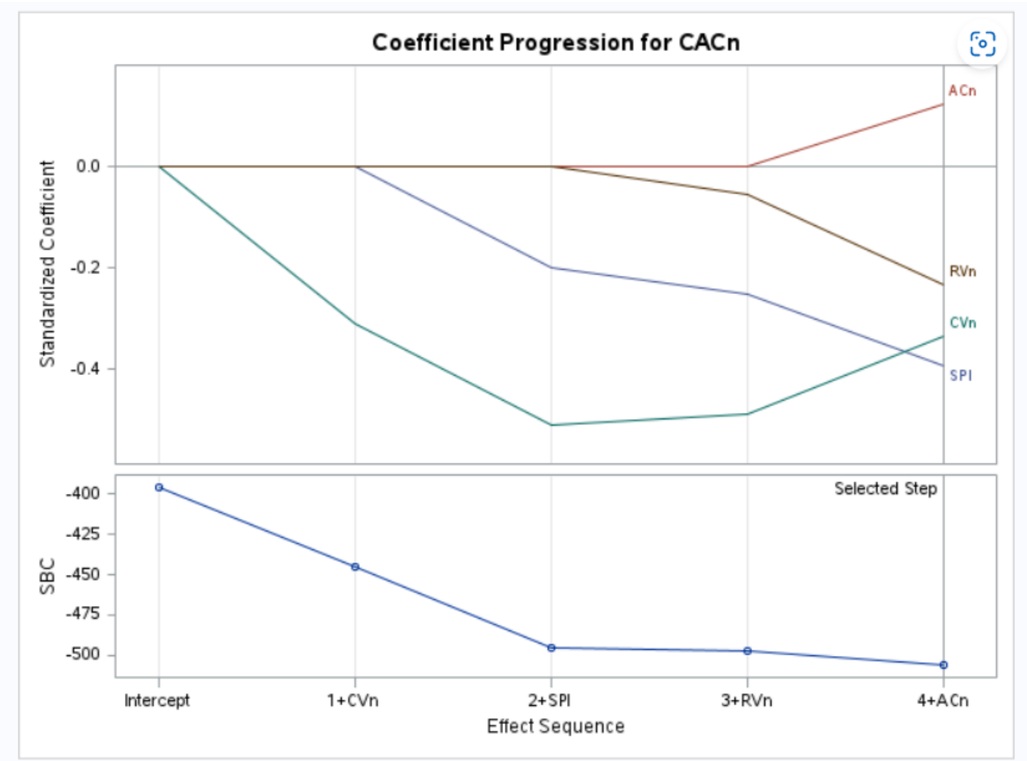

Figure 15 - LASSO solution path Blue Team dataset
(Source: SAS® Studio)

In order to get the optimal SBC, only four steps in this case were required, until the minimum value of - 506,22 was registered. Table 13 representing the LASSO selection summary better visualizes how the procedure stops when the TPn coefficient wants to enter in the regression model, yet not allowed since the stop criterion would increase its value. In addition, there are no situations where an effect firstly enters and is consequently removed as happened in previous cases, hence all four entered effects are kept in.

Table 13 - LASSO selection Blue Team Dataset
(Source: SAS® Studio)

The GLMSELECT Procedure

LASSO Selection Summary				
Step	Effect Entered	Effect Removed	Number Effects In	SBC
0	Intercept		1	-395.6084
1	CVn		2	-445.4274
2	SPI		3	-495.9308
3	RVn		4	-497.4467
4	ACn		5	-506.2198*
* Optimal Value of Criterion				

Selection stopped at a local minimum of the SBC criterion.

Stop Details				
Candidate For	Effect	Candidate SBC		Compare SBC
Entry	TPn	-501.7512	>	-506.2198

Eventually, the variance of $CACn$ is expressed by: $SPI, ACn, CVn, and\ RVn$.

The first regression is run, and the ANOVA can be interpreted. Even though the model expresses an overall statistical importance, as in the full dataset first regression attempt one regressors has got a p-value greater than 5%. The regressor under examination is once again the CVn with a p-value of 0,054. Having understood its small contribution in explaining the Cost at Completion (that happened not only for the Blue Team but also for the two previous cases), the GLM procedure is repeated discarding it from the selected variables.

FINAL MODEL

The Blue Team definitive model is stated by:

$$CACn = f(SPI, ACn, RVn)$$

The final linear regression is performed, and the ANOVA is interpreted.

Table 14 - ANOVA Blue Team sub-set
(Source: SAS® Studio)

The GLM Procedure

Dependent Variable: CACn CACn

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	2.37927687	0.79309229	75.97	<.0001
Error	111	1.15885397	0.01044013		
Corrected Total	114	3.53813084			

R-Square	Coeff Var	Root MSE	CACn Mean
0.672467	9.828832	0.102177	1.039563

The overall significance is confirmed by the F-statistics with a value of 75,97 and p-value lower than accepted null hypothesis threshold. However, the Blue Team model is the least in term of utility, since the latter expresses a value of significance smaller than the former analyzed statistical models. Furthermore, the R-squared confirms a good fitting with an explained portion of variance equal to 67%, yet smaller than the full programme statistics and Green Team's one. The beta coefficients parameters estimate of the selected regressors are reported in Table 15.

Table 15 - Slope estimations Blue Team model
(Source: SAS® Studio)

Parameter	Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	1.711595589	0.06613964	25.88	<.0001	1.580535470	1.842655708
SPI	-0.801756464	0.07227039	-11.09	<.0001	-0.944965069	-0.658547860
ACn	0.155715059	0.03165769	4.92	<.0001	0.092983242	0.218446876
RVn	-1.181647468	0.12739837	-9.28	<.0001	-1.434095853	-0.929199084

$SPI, ACn\ and\ RVn$ are all characterized by statistical importance, how observed from their p-values and t-statistics for calculating $CACn$. From the correlation analysis evidence of the Blue Team, it can be said that the multicollinearity is not present in the model, in fact no relationships exist between the three independent variables.

2.5. How to evaluate effectiveness

The statistical predictive models have been determined so far. Now the goal is to find a way for assessing them in terms of their performances to compute estimations of $CACn$ in the three different purposed scenarios.

The forecasting methods are validated based on their accuracy. The accuracy is the most important concern when evaluating forecasting quality (Ryu and Sanchez, 2003). Being the observations of the variables already in percentage terms through the application of the normalization procedure, the best the appropriate indicator to assess the accuracy is the Mean absolute error (MAE). It gives an indication of the degree of spread, where all errors are assigned equal weights. The formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

where n is the number of observations in the dataset and e_i is the residual so the difference between the real $CACn$ and the predicted $CEACn$ in absolute terms at each n. When e_i is a negative value, it means overestimation in comparison to the real one, when positive stands, on the other hand, for a situation of underestimation. If the predictive model fits the real outcomes very well the MAE will be closer to zero, in case of poor fitting, instead, MAE will be large. Thus, when two or more forecasting methods are compared, the one with the minimum MAE can be selected as most accurate (Ryu and Sanchez, 2003).

The second parameter necessary to evaluate the effectiveness is the Standard Deviation (SD). Its value gives an indication of the statistical dispersion of the e_i residuals from the average forecast of the dataset under examination (Sanjoy, 2011). To compute SD, it is required the formula:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(e_i - Mean(e))^2}{n}}$$

where the term under square root is the variance, thus the average of the squared differences between the error i of an individual observation and mean of all the errors. The smaller value of SD, the more precise the cost estimates (since estimation errors are closer to the dataset average error). The SD outcome, in line with the accuracy level, might be an incentive to the Software Testing PMO to introduce the models derived from linear regressions as the ones to use in estimating the final project cost.

The next step is benchmarking the accuracy and precision of the Programme, Green Team and Blue Team regressed model with the Index-Based $CEAC$ computations to verify whether the implementation of the new discovered models is worth. The EVM Index-Based methods are seven in total, and they come from the literature presented in this dissertation. However, a summary table briefly recaps them here:

Table 16 - CEACn Index-based to benchmark with the linear regression approach (Source: author)

EVM	APPROACH	INDEX-BASED FORMULA
EVM_1	INITIAL BUDGET	*CEACn=BACn*
EVM_2	ORIGNIAL ESTIMATE	*CEACn=BACn-CVn*
EVM_3	REVISE ESTIMATE	*CEACn=BACn/CPI*
EVM_4	PESSIMISTIC	*CEACn=BACn/(CPI*SPI)*
EVM_5	ALTERNATIVE PESSIMISTIC	*CEACn=BACn/ (.8 CPI + .2 SPI)*
EVM_6	PESSIMISTIC - ES ITEGRATION	*CEACn=BACn/(CPI*SPIt)*
EVM_7	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	*CEACn=BACn/ (.8 CPI + .2 SPIt)*

As it can be noticed from the table, EVM_6 and EVM_7 are two other ways to compute the Cost Estimate at Completion that differ from EVM_4 and EVM_5 considering their integration of the Schedule Performance Index $(SPIt)$ derived from the Earned Schedule approach. These formulae have been applied in the weekly monitoring of the projects and they constitute the n data of the three scenarios after that same polishing approach, as applied in correlation analysis and linear regression, was put in place. As well, for the index-based $CECAn$ the errors are determined, thus MAE and SD calculated. The goal will be not only assessing if the linear regression fitted models are more accurate and precise than Index-based ones, but also providing a ranking from the most to the least efficient predictive approach. The current reference formula for the PMO of the Area Credit Programme is the EMV_3, in fact it will be interesting to analyze in which position of the classification its outcome will be ranked.

CHAPTER 3. FINDINGS AND DISCUSSION

This section provides for final results and discusses about possible implications. Always considering the entire programme and the team subcategories, the focus will be:

- Description and comparison of the three fitted models
- Accuracy and precision outcomes when benchmarking against the Index-Based approaches
- Assessing and commenting on the diagnostics of the models' fit.

Finally, implications, limitations and hacks for further investigations are presented.

3.1. Fitted models

3.1.1. Programme Predictive Model

The fitted model to calculate the Cost Estimate at Competion at a programme level is:

$$CACn = 1.80133 - 0.28831SPI - 0.66234RFI + 0.23032ACn - 0.99899SVn$$

It is noticeable that the conclusions made during the correlation analysis between variables are all confirmed. Specifically, the SPI is verified to have a moderate negative correlation with the dependent variable, as increased by unitary percentage, keeping constant all other features, the $CACn$ diminishes by almost 0.3 unit. It confirms again the hypothesis that the more the time saving, the less the final cost. This might be a bit ambiguous in general terms, since a SPI indicator greater than 1 not always mean that the project is saving on budget, for instance when crashing activities is applied, which means having a greater pace but at the same time involving more resources to make it possible. Considering the RFI regressor influence on the Y, confirmed is its quite heavy negative association. When it increases by one unit%, the Cost at Completion drops by 0.66, while others stay constant. Again, the initial PMO's hypothesis is confirmed: more correctly and precisely the managerial staff is in the resource allocation, balancing the workload on the elapsed and estimating the projects' efforts, the lower is the possibility of cost increase.

The third negative correlated regressor is the SVn, underlining its characteristic of being a variance parameter fundamental in computing predictions of $CACn$. When all other variables are kept constant, a unit percentage increase in schedule variance performance means reduction of almost the same quantity the cost at completion estimate. Hence, the monitoring and interpretation of this feature has to be very accurate for the programme stakeholders. With two-time variables involved in the predictive model, it can be highlighted the importance of not exceeding the Planned Duration (PD) in software testing environment. The reason behind such a behavior could by represented by the importance in this kind of project to stick to the established timeline, since the go-live and time to production is most of the time a milestone that cannot be absolutely postponed from the client side.

$SPI, RFI\ and\ SVn$ all express negative weights, therefore, a weighted sum of the three variables must be made. The independent variable that helps counterbalancing their negative effects is the ACn. In this case, the latter percent unit increment would lead an output increase of one fourth, being the rest univariate. The initial positive correlation hypothesis is confirmed one more time, even though, due to its high variability during the projects' monitoring activities, it remains a moderate contribution. The intercept of 1.8 is the value of $CACn$ when all variables are equal to 0. In this study, this value assume solely geometrical meaning since if the four selected parameters explaining the portion of variance of the Y under examination have null value it would signify that the project is not started yet, therefore there is no sense to estimate the value of the final cost without the registration of any activity progress.

Furthermore, by having performed LASSO, $TPn, WS, WP, and\ ESn$ are confirmed, as for the correlation analysis, not to be fundamental to compute final costs. A particular remark, instead, can be made for the $CPI, CVn\ and\ RVn$ variables whose correlations with the ACn (ADn) were verified to be strong negative. The fact that these features are not involved in the regression states that the other ones included instead in the predictive model express much more importance and are exhaustive in explaining the variability of the outcome, accordingly the former tend to be eliminated by the shrinkage. This is in line with the LASSO goal of finding the model as simple and efficient as possible, avoiding redundancy and poor associations while solving for multicollinearity. In this case the LASSO selection procedure ignores variables that have a strong correlation with $CACn$, but that poorly contribute to the variance significance in the context where other features are considered, thus not giving additional information. This is the case of CPI, initially selected and successively discarded at step seven, hence showing an ambiguous behavior considered at the end not necessary to be included, as well as for RVn never been embedded throughout the process before the SBC reached its local minimum. Unlike these two, the CVn was initially considered as a variable whose coefficient has not been shrunk towards zero, notwithstanding discarded during the paraments estimate phase due to its p-value that showed not statistical significance in explaining the variance of the dependent variable.

Table 17 - Comparison Correlation analysis and fitted model full programme dataset (Source: author)

Variable	Correlation Importance	Fitted Model coefficients
TPn	No correlation	N/A
WS	No correlation	N/A
WP	No correlation	N/A
ACn	Moderate positive	0,23032
CPI	Strong negative	N/A
SPI	Moderate negative	-0,28831
CVn	Strong negative	N/A
SVn	Moderate negative	-0,99899
RFI	Strong negative	-0,66234
RVn	Moderate negative	N/A
Esn	No correlation	N/A

3.1.2. Green Team Predictive Model

Looking at the Green Team sub-set the determined fitted model is:

$$CACn = 1.66036 - 0.78678RFI + 0.22616WS - 1.63367SVn$$

When the goal is to determine a fitted model to estimate the Cost at Completion based on the Green Team historical data, the number of significant regressors drops to three. The importance of involving the account discrepancy index RFI and the schedule variance SVn is one more time confirmed with even greater weights than before. In fact, when the former increased by one unitary percentage, having the other two regressors constant, the cost estimate falls by approximately 0,79 highlighting how the variable paly a very important role in prediction power. Even more fundamental is the monitoring of the schedule variance, while it increases by one percent, keeping the rest constant, the $CACn$ is going to diminish as much as 1,63367. This consistent value again highlights how in the testing projects is very fundamental with respect to what has been planned (so that the $BCWS/ACWP$ must turn to be greater than the unity) and the that the progress of the project must be in line with what was expected by the client. The planning phase is so relevant for the Green Team projects, in fact the WS is the third model's explanatory feature. With a coefficient equal to about 0,23, once the percentage of the scheduled progress increments by one, the $CACn$ is subject as well to a rise of one fourth, having the previous two variable unchanged. Here the case is singular since the initial PMO's hypothesis is not respected, moreover the outcome is not in line with the correlation analysis of the sub-set under examination whose value stated that no correlation was verified.

The discussion held above allows to stress how the variable relationships might be different when diverse data subcategories are analyzed. This is because it happens that the project conditions and specifications are oftentimes divergent up to each team and types of works to be done. Therefore, WS seems to play a role in determining the final cost in the second scenario while is not the case in the programme general dataset and for the projects belonging to the Blue Team. This important finding supports the mission of the conducted analysis and emphasized that when dealing with a group of related projects with a central authority holding the control over such a programme or portfolio, if the conditions permits the analysts to find a discrimination factor to sub-divided the activities, there could come the advantage of better determining estimation models whose outcomes would better perform and being more adapted in the specific sub-context. Returning to case study and having determined these implications, the PMO might be able to promote the new statistical prediction to the sole Green Team for its future releases.

From the LASSO results the discarded variables are eight in number, as it can be visible in the recap table presented below. The reasons why this happened, and the related justifications are the same presented in the previous paragraph, indeed they can be applied for the sub-set analysis as well. As explained in in the methodology section, for the Green Team all discards have been directly determined by the LASSO fit and no other was eliminated by considerations made at the time of slopes significance determination.

Table 18 - Comparison Correlation Analysis and fitted model Green Team sub-set (Source: author)

Variable	Correlation Importance	Fitted Model coefficients
TPn	No correlation	N/A
WS	No correlation	0,22616
WP	No correlation	N/A
ACn	Moderate Positive	N/A
CPI	Strong Negative	N/A
SPI	Moderate Negative	N/A
CVn	Strong Negative	N/A
SVn	Moderate Negative	-1,63367
RFI	Strong Negative	-0,78679
RVn	Strong Negative	N/A
Esn	No correlation	N/A

3.1.3. Blue Team Predictive Model

The fitted model of the Blue Team sub-category is:

$$CACn = 1.71159 - 0.80176SPI + 0.15572ACn - 1.18165RVn$$

At a first glance it is immediately clear that the predictive model differs from the one of the Green Team. First of all, the intercept value is slightly higher but, as it could have been expected, lower than the full dataset one. In terms of regressors the $SPI, ACn, and\ RVn$ represent the fundamental observations that have the characteristics to explain the final cost variance whose coefficients' directions are all in line with the initial PMO's hypothesis.

For a unit change in SPI, the $CACn$ estimate drops by 80%, keeping constant the other two variables. It seems that full dataset inherits the SPI significance from this team. Even stronger negative relationship is the one with the RVn. By a unit increase in the latter and as usual keeping univariate the others, the cost at completion will drop by an amount more than the unit. One can see that this is the first time the feature RVn is selected as explanatory variable, replacing its index version RFI, always present in the pervious predictions. The resource variance observations, in this case, are more sensible in entering the model, the greater they are the better the cost accounting performances leaving aside the project progress.

The actual cost plays a role too. Specifically, the variable is positively correlated with the cost at completion, therefore when it modifies by a unitary increase, while schedule index and resource variance stay univariate, the model outcome is subject to an increase of 15%. The consideration is in line with the PMO's insights since if the actual cost to bear is more in value, in turn the final actual cost at actual duration will follow the same trend. The ACn importance at the programme level regression is inherited by the Blue Team projects, whereas $RFI\ and\ SVn$ come from the Green Team influence and remain important in explaining the dependent variable in the overall dataset. On the other hand, the variables $RVn\ and\ WS$ have shown particular importance in the teams, respectively Blue and Green, but do not constitute a selected variable of the programme total statistical projection.

The features not included in the model have been discarded by the LASSO or by the parameters estimate p-values greater than the significance acceptable threshold (as the case of CVn). Even in this case, what stated in the previous paragraph is valid. In comparison to the simple correlation analysis, the regression considers the weight that each regressor expresses in the fitted model of the Y and their combinatorial effect. Hence, the influences of all the variables present in the model explains why the initial correlation results from $CACn$ and one feature it does not translate into a significant association in the fitted model. This is what LASSO does when shrink and regularizing coefficients. In addition, it can be reported that, neither in terms of correlation analysis nor in the regression construction the variables $TPn, WP, and\ ESn$ have a significance in explaining Cost estimate at Completion in the specific case study. $CPI\ and\ CVn$, on the other hand, if taken individually are highly correlated with the dependent variable, however in the fitted model determination, due to their ambiguous not constant behaviors over time, are never preferred over other variables as more explanatory terms to conduct predictions.

Table 19 - Comparison Correlation Analysis and fitted model Blue Team sub-set (Source: author)

Variable	Correlation Importance	Fitted Model coefficients
TPn	No correlation	N/A
WS	No correlation	N/A
WP	No correlation	N/A
ACn	No correlation	0,15572
CPI	Moderate Negative	N/A
SPI	Moderate Negative	-0,80176
CVn	Strong Negative	N/A
SVn	Moderate Negative	N/A
RFI	Moderate Negative	N/A
RVn	Moderate Negative	-1,18165
Esn	No correlation	N/A

One more time is reflected the fact that the model of a sub-set can differ from another. Even though under the same programme umbrella, teams are diverse and characterized by the project nature, requirements, priorities and adopted strategies to complete the required deliverables. Test Managers are distinct, as well as team members such as Test Analysts, Testers and PMO reference. The predictive models consider the peculiarities of each dataset. The fact of having individually analyzed three scenarios surely constitute an advantage that comes from the fact that each group can apply its own predictions with a model that better suits their environment, taking in consideration more informed and personalized needs and operative conditions. The programme formula, instead, is supposed to be used in a more general context, when for instance a project is new to one of the teams or for works that involve both of them, or, in addition, can be used by the PMO, in accordance with the Service Manager and Technical Direction, to make esteems on the overall programme evolution. Strategic decisions, planning and risk management are all supported by the new approach. It is possible to identify, as such, best practices and behavioral peculiarities to enhance the overall projects' performances.

In summary, the full dataset predictive model can provide a general overview and high-level information to support program-level decisions, where common relationships between variables can impact the effectiveness and efficiency of the entire software development program.

3.2. Accuracy and Precision

The final objective is to evaluate whether the predictive models better estimate the Cost at Completion in the three purposed scenarios through accuracy and precision. A comparison is made with the index-based methods as explained in the previous chapter.

FULL DATASET

Starting from the benchmarking of the programme predictive model, comparative tables are presented.

Table 20 - Accuracy and Precision comparison programme dataset (Source: author)

	APPROACH	PREDICTIVE MODEL	MAE	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn= 1.80133 -0.28831SPI-0.66234RFI+0.23032ACn-0.99899SVn	0,09758	1
INDEX-BASED METHODS	ORIGNIAL ESTIMATE	CEACn=BACn-CVn	0,13189	2
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,21407	3
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,21693	4
	INITIAL BUDGET	CEACn=BACn	0,22017	5
	REVISE ESTIMATE	CEACn=BACn/CPI	0,22386	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	0,53316	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	0,55335	8

	APPROACH	PREDICTIVE MODEL	SD	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn= 1.80133 -0.28831SPI-0.66234RFI+0.23032ACn-0.99899SVn	0,13018	1
INDEX-BASED METHODS	ORIGNIAL ESTIMATE	CEACn=BACn-CVn	0,17546	2
	INITIAL BUDGET	CEACn=BACn	0,26719	3
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,34640	4
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,34791	5
	REVISE ESTIMATE	CEACn=BACn/CPI	0,38837	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	1,08250	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	1,09268	8

As it can be observed, the linear regression outperforms the index-based for both the benchmarking criterions, having the lowest value of MAE for assessing the accuracy and the lowest value of SD for assessing the precision. The evidence underlines the limitations of the index-ones that are up to backward looking analysis and past EVM data. The BAC is adjusted by performance metrics that considers the project to continue at its current status until the closure. As reported in literature, this means that the schedule and cost performance remain unchanged for the rest of the activities.

Even when the pessimistic and alternative pessimistic approaches are integrated with the ES, thus dividing the BAC by schedule index in term of time trying to solve lack of information about possible delays to optimize the programme, the MAE is noticed to get an improvement but still the regression analysis is confirmed to be better. The latter might better catch uncertainty and changes during the project life for instance in the early stages when the traditional performance indexes have been proven to fail in providing stable values. Likewise, precision is confirmed to be at its best in the statistical prediction with a value of 13%. This finding is in line with what has been observed from literature about the outranking performances of the linear and nonlinear models with respect to the IB forecasting, whose estimates tend to be less accurate and precise. It is noteworthy that, in most of the projects, irrespective of their characteristics, financial resources, or duration, projections made using a conventional methodology tend to stabilize only during the latter stages or the second half of the project's lifespan, while the linear regressions might help the programme managers to determine improved predictions on the overall elapsed.

Even though from one side it is suggested to use the regression method as the one that provides the most reliable information, it is also remarkable how the Original Estimate approach might be a valid alternative, given the fact that its MAE and SD deviate form the best ones just by 3,5% and 4,5% respectively, in turn ranking as the second classified for both the assessment criterions. Although this is not the best way to pursue since it is still a predictive approach under the past data bias and cost variance that is assumed to stay univariate in the future evolution, still in term of difference between observed and estimated data represents the one among the index-based with the lowest MAE and SD, therefore is surely more recommended that the one currently applied by the PMO. In fact, the Revise Estimate poorly ranks in both terms listed as the sixths positioned.

GREEN TEAM SUB-SET

The procedure is repeated for the dataset created by the five Green Team projects with the aim of verifying whether the same results might be obtained. In the following table the MAE and SD comparison is presented.

Table 21 -Accuracy and Precision comparison Green Team sub-category (Source: author)

	APPROACH	PREDICTIVE MODEL	MAE	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn=1.66036-0.78678RFI+0.22616WS-1.63367SVn	0,1011	1
INDEX-BASED METHODS	ORIGINIAL ESTIMATE	CEACn=BACn-CVn	0,1818	2
	REVISE ESTIMATE	CEACn=BACn/CPI	0,2789	3
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,2808	4
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,2834	5
	INITIAL BUDGET	CEACn=BACn	0,3094	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	0,7183	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	0,7369	8

	APPROACH	PREDICTIVE MODEL	SD	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn=1.66036-0.78678RFI+0.22616WS-1.63367SVn	0,1316	1
INDEX-BASED METHODS	ORIGNIAL ESTIMATE	CEACn=BACn-CVn	0,2133	2
	INITIAL BUDGET	CEACn=BACn	0,3286	3
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,4289	4
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,4297	5
	REVISE ESTIMATE	CEACn=BACn/CPI	0,4709	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	1,4292	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	1,4230	8

The results already found from the entire programme database are confirmed, in fact the linear regression model is the one that records the lowest Mean Absolute Error and Standard Deviation. Therefore, EAC forecasting accuracy is improved, while error variance is reduced. The model is validated and could be implemented in the monitoring and controlling activities held by the PMO in partnership with the Green Team.

Looking at the Index-Based methodologies, the Original Estimate once again is in the forefront in terms of quality of prediction, even though this time the discrepancy from the regression base is approximately equal to 8% for either MAE or SD.

The Revise Estimate currently used by the management is suggested to be abandoned. Moreover, the index ES approaches do not constitute reliable predictions given by the fact that there are others presenting better efficiency. The Pessimistic, with and without the ES integration, still deliver the worst degree of spread and error variance.

BLUE TEAM SUB-SET

Table 22 presents the comparison analysis for the Bule Team observations and ranks all the methods analyzed.

Table 22 - Accuracy and Precision comparison Blue Team sub-category (Source: author)

	APPROACH	PREDICTIVE MODEL	MAE	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn=1.71159-0.80176SPI+0.15572ACn-1.18165RVn	0,07287	1
INDEX-BASED METHODS	ORIGNIAL ESTIMATE	CEACn=BACn-CVn	0,08155	2
	INITIAL BUDGET	CEACn=BACn	0,13012	3
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,14676	4
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,14988	5
	REVISE ESTIMATE	CEACn=BACn/CPI	0,16838	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	0,34640	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	0,36820	8

	APPROACH	PREDICTIVE MODEL	SD	RANKING
REGRESSION-BASED METHOD	LINEAR REGRESSION	CACn=1.71159-0.80176SPI+0.15572ACn-1.18165RVn	0,1008	1
INDEX-BASED METHODS	ORIGNIAL ESTIMATE	CEACn=BACn-CVn	0,1197	2
	INITIAL BUDGET	CEACn=BACn	0,1762	3
	ALTERNATIVE PESSIMISTIC - ES INTEGRATION	CEACn=BACn/ (.8 CPI + .2 SPIt)	0,2201	4
	ALTERNATIVE PESSIMISTIC	CEACn=BACn/ (.8 CPI + .2 SPI)	0,2237	5
	REVISE ESTIMATE	CEACn=BACn/CPI	0,2720	6
	PESSIMISTIC - ES ITEGRATION	CEACn=BACn/(CPI*SPIt)	0,4942	7
	PESSIMISTIC	CEACn=BACn/(CPI*SPI)	0,5211	8

The research goal is confirmed in the Blue Team case too, in fact the linear regression approach represents for the third time the highest-ranked between the index-based comparisons. Hence, also for their type of projects it is highly suggested to introduce the novelty to better estimate the Cost at Completion.

Looking at the behavior of the Original Estimate approach, it can be emphasized that, in this scenario, its MAE is much more in line with the most accurate model, being their discrepancy only about 1%. The same thing happens for the model precision, since the SD is worse by 2% only. Therefore, the PMO, in accordance with the team, can somehow consider this model to be a good substitute of the statistical predictive one even if the latter should be always theoretically preferred.

In addition, the Revise Estimate Approach can be said to not efficient as the above two, being in the sixth position in both rankings. Hence, the current forecasting, once more time, should be discarded. The worst two are verified to be, as for the previous scenarios, the Pessimistic and the Pessimistic with ES incorporation.

3.3. Diagnostics of fit

To evaluate the consistency of the models, some tests on residuals were carried out. First of all, in order to assess the diagnostics of the model fit, the regression assumptions are going to be checked. Three plots are provided by SAS® for this purpose:

- Residuals against predicted values: to verify that no patterns, time series or periodicity is present.
- Residuals against quantiles: to check for the linearity of the regression.
- Residuals distribution: to confirm that the residuals are normally distributed.

Other interesting findings to check for model bias might be denoted by:

- Real against predicted values: to observe the magnitude of underestimation and overestimation.
- Residuals against the regressors: to verify residuals' behavior by the regressor value range.

As for the previous sections, results for all the analyzed scenarios will be outlined.

FULL DATASET

As it can be seen form Figure 16, the linear regression assumptions are respected when considering the totality of the observations to perform the general regression model.

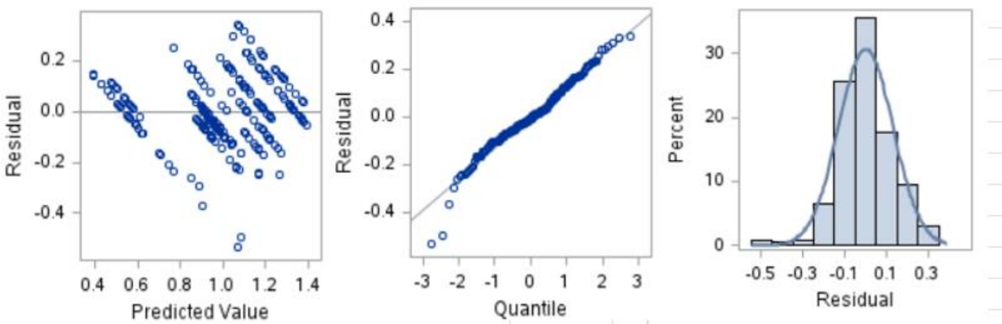

Figure 16 - Verified regression assumptions for the Full Dataset (Source: SAS® Studio)

Form the left figure, some form of real patterns might be denoted so that the fit could be probably revised, however in broad terms and for the purpose of this dissertation it can be considered acceptable. The center figure says that linearity assumption is confirmed, while the right one assures the normal distribution of the residuals. Furthermore, Figure 17 presents the quality of prediction plotting the real data against the predicted ones for each observation.

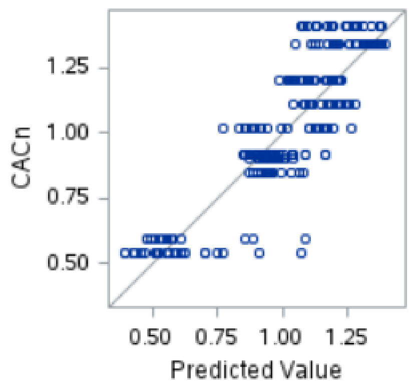

Figure 17 - Model bias full programme
(Source: SAS® Studio)

The errors are mostly determined by the bias in the project performance metrics that are based on past data, assumed to be constant until the project end, hence failing in considering future project dynamics and by the fact that that their reliability is not guaranteed in the initial phase. Form the totality of 231 observations, the overestimations are counted to be 119 with a negative average error of 0,0947 and a negative maximum of 0,5343. The underestimation cases are slightly lower with a positive average of 0,1 and a maximum value of 0,34.

Finally, Figure 18 reports the behaviors over the regressors' values. The SPI shows that the weekly reporting are mostly behind the schedule and rarely ahead. It must be reminded that the time index is the one in monetary terms that fails to give good information when the project approaches its end, especially in situation in which the project does not finish on time and schedule deviation is not observable. By this end it can be understood the condensation of many points among the value of 1, justified also by the fact that none of the projects in the dataset finished with a big delay due to the go-live constraint (just a matter of few weeks delay for some of them). Similar considerations can be affirmed for the SVn.

In terms of ACn it can be said that, as it increases, the more the project approaches its final effective total costs, the less the residual variability. Its presence is fundamental in balancing the weighted negative effect of the other three regressors. Not many values are greater than one in this case, confirming how in most projects there have not been registered cost overruns, and if yes, by small amounts. About RFI, no particular behavior is found.

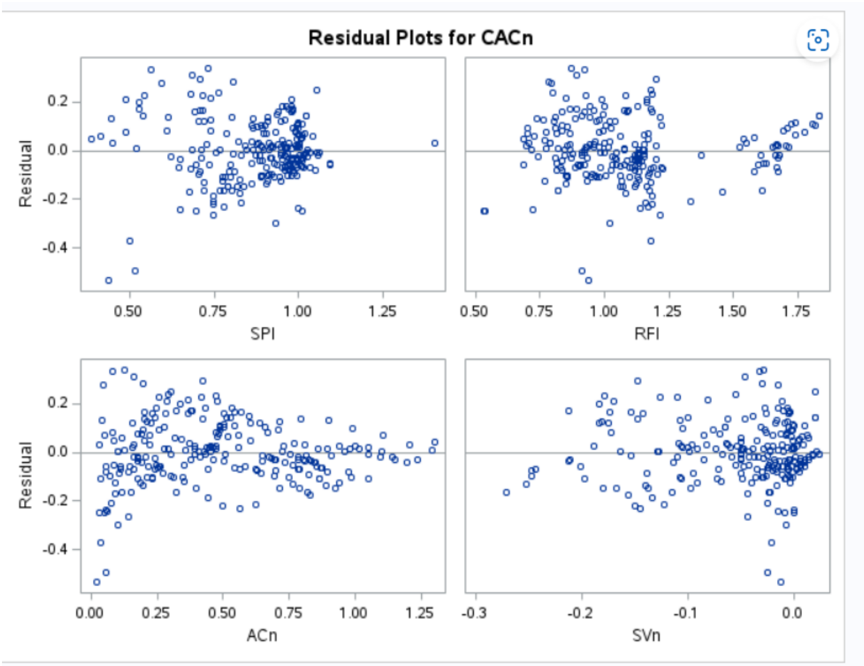

Figure 18 - Residuals over regressors total dataset
(Source: SAS® Studio)

GREEN TEAM DATASET

The linear regression applied to the Green Team, being a sub-category of the previous dataset, respects the linearity assumptions too.

The observations are counted to be as much as 116. From the real vs predicted values overestimations and underestimations are observed. They divide the prediction in 50% to be overestimated and 50%, on the contrary, underestimated. The average error for overestimation is a negative value of 0,1011 while its maximum is registered at 0,4103. The second phenomenon has the same value in average, even if this time positive, and a maximum positive of 0,2691.

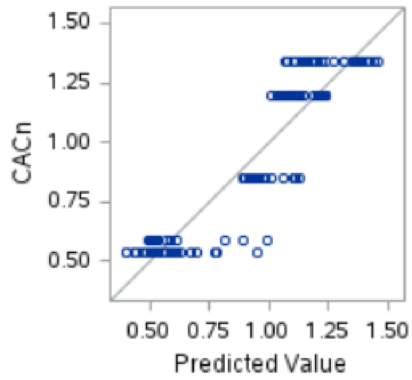

Figure 19 - Model bias Green Team sub-set
(Source: SAS)

The residuals against the regressors might be explained following the same considerations abovementioned. The main difference here is the presence of the WS in explaining the dependent variable. The work scheduled counterbalances the negative weighted sum between $RFI\ and\ SVn$. It is visible how following the project completion, the progress tends to one determining less risks, in turn less deviations between predicted and actual values of the dependent variable.

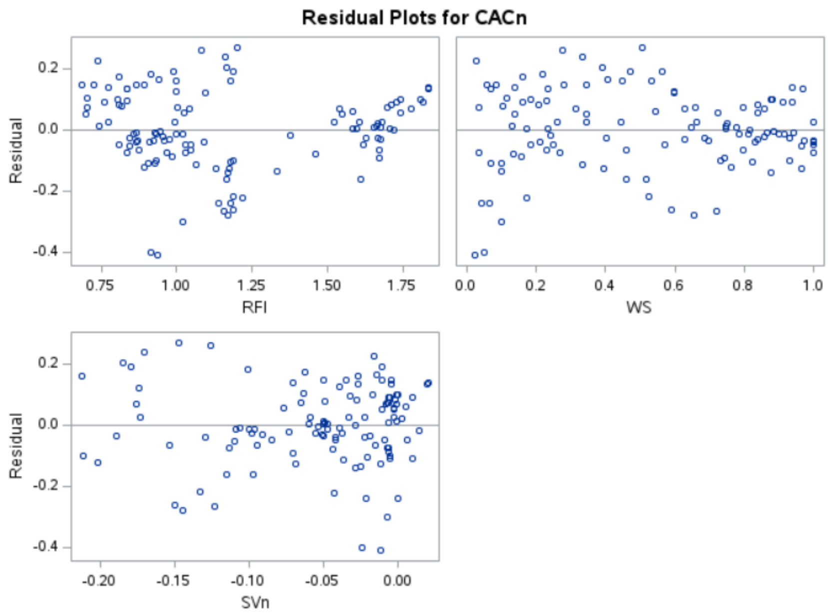

Figure 20 - Residuals against regressors sub-category Green Team
(Source: SAS® Studio)

BLUE TEAM DATASET

The same type of diagnostics analysis is conducted for the second sub-category represented by the Blue Team. Also, in this last case, linearity assumptions have been checked.

The same considerations can be outlined for the fitted model bias, as reported in the previous scenarios. On the total of 115 observations, overestimations are 57%. Their average is limited, whereas the maximum is a negative error of 0,3. The underestimation phenomenon shows greater values in the investigated category of data in terms of average that anyway remains still lower than 10%, while the maximum positive error is similar to the one of over esteem.

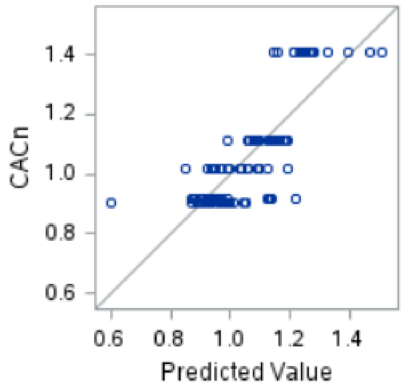

Figure 21 - Model bias Blue Team sub-set
(Source: SAS® Studio)

The last step is to check for the residual plots over the value range of the regressors with the aim of observing any possible bias behavior due to the nature of the EVM variables. Even if with less data, $SPI \text{ and } ACn$ show, as expected, the same residual distribution as in the previous cases. About the RVn it is noticeable how the accounting discrepancy is many times equal to zero or even positive, showing that the Blue team did not suffer much from erroneous effort estimations or wrong planning of resource allocation. The errors tend to increase when the variable is negative and stabilize to zero with its positive values. Once again this might be another proof that bias exists due to project stages and nature of the variables. The actual cost mitigates the negative contribution of resource variance and schedule index.

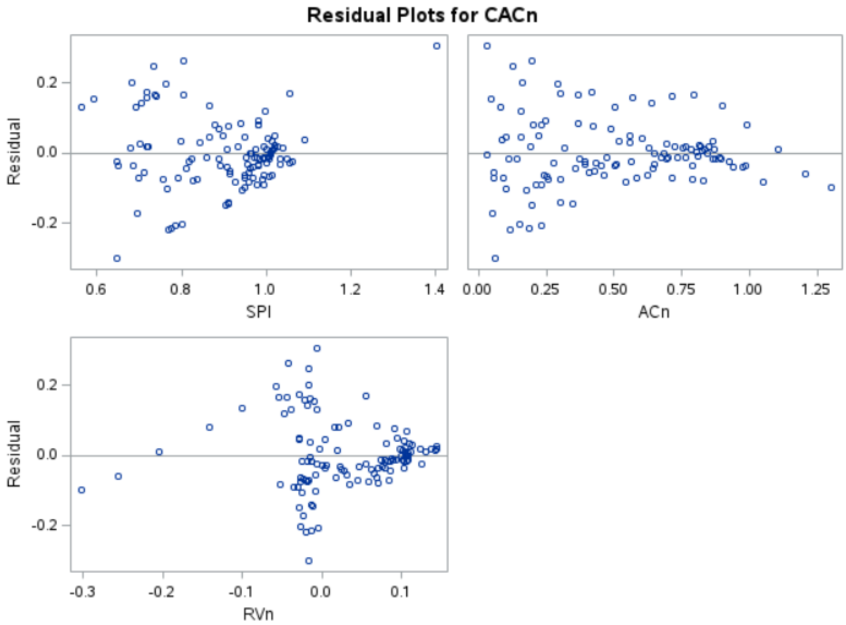

Figure 22 - Residuals against regressors sub-category Blue Team (Source: SAS® Studio)

3.4. Limitations and further research

One of the most important limitations of the study is that it requires historical data in terms of progress, cost and schedule metrics collected by the project teams. When the latter are not, for any reason, available, it will be difficult for the staff management to perform the EVM and determine predictive models. It could be difficult to use the proposed techniques for those who do not have at disposal certain datasets. Thus, an organization that wants to structure similar analysis is supposed to gather enough projects belonging to a programme. The dataset construction must be accurate and reliable in order to run regressions.

Another important research limitation to underline is the fact that only a specific case study of a 10-project program is involved in the analysis, thus there is the need to enlarge the dataset under examination to make the results and implications more valid and robust. It has to be stressed that a relatively small sample size could failure to capture the right relationship among variables. Furthermore, with the aim of extending the applicability to other industries, the additional data to be embedded should come from different sectors and area (remaining anyhow in the technology and digital services context), indeed, to being capable to generalize what has been concluded in the dissertation. The demonstrated bias call for implementation of even diverse data selection procedures and comparison between them to denote which one might be the best to enhance predictive power and statistical significance.

Furthermore, the analysis is based on correlational designs, therefore simultaneous causality problems must be accounted and better interpreted. Further research might think to establish causality dimensions for the variables. It is also important to remember that EVM indicators are limited in addressing quality, risk, opportunity, uncertainty, and skills. Even though the prediction improvement has been demonstrated, the linearity assumptions have to necessarily be hold, for instance the one of linear relationship between the variables.

Although the R-square of the three predictive models show quite large percentage of the variance explained, for further research on the proposed topic nonlinear regression model might be applied to improve the forecasting accuracy and precision. As previously mentioned, nonlinear models and machine learning algorithms can enhance the predictive power on cost and time, furthermore, EMV metrics are indicators whose association with $CEAC\ and\ TEAC$ more properly works when these frameworks are established. Random effects models of panel data might be a solution in this case.

Another improvement might be constituted by utilizing other statistical methods such as the Monte-Carlo simulation, which considers performance metrics as random variables to be sampled from historical data distributions with the aim of improving the estimates. Bayesian statistics can be applied too. The advantage here is the involvement of real-time data to update $CEAC$ distribution (Kim et al., 2011). Comparison between regressions and these kinds of statistical approaches could be interesting to arrange for further system validation. Artificial intelligence is also a promising implementation in the project management field. Models like Artificial Neural Network (ANN) and fuzzy logics might deeply being studied and benchmarked against the author's purposed prediction patterns with the objective of determining a good trade of between accuracy, variance, and difficulty in application.

When instead the idea is to continue further with the regression-based frameworks improvement, other variable types, omitted in the proposed dissertation, might be accounted that are diverse with respect to project performance indicators. An example might be the implementation project risk-related variables to better explain the variability of the cost and time estimations. In this way, considerations on uncertainty over the $CEAC\ and\ TEAC$ can be outlined. External factors could also be considered, not only in terms of project risks but also parameters such as economic changes and market conditions.

CONCLUSION

One of the most important objectives of the project and programme monitoring and controlling is to perform Estimate at Completion to evaluate whether there is room for applying in-time corrective actions that lead to stay within the budget and time at disposal for the activities. This is the reason why this study, in line with existing literature and various investigations, contributes to improve the Cost Estimate at Completion by focusing on analyzing its behavior from a programme scenario point of view. Firstly, the programme level general predictive model might be beneficial for company considering its applicability to similar ones in the context of medium-length IT Software Testing projects. Secondly, the team-based linear models can be beneficial for the two main kinds of Area Credit stream of activities denoted by the variables, among all the EVM and ES possible ones, that explain the most the effective final cost. To denote the final results the collection of data through EMV monitoring was necessary, as well as the study of the existing correlation between the variables, the LASSO procedure to choose the most proper ones, and, finally, model properties to analyze the multiple linear regression significance and validity. The proposed methodology, considering the team-based regression differentiation as well, might be used as a driver of similar approaches to be adopted to monitor similar datasets.

Moreover, the research emphasizes and recommends the use of statistically validated frameworks with respect to the most used index-based traditional techniques that heavily rely on past data, whose accuracy and precision has been verified to be lower than the author's proposal prediction models. Once again this is especially beneficial in medium-term duration projects which require something more sophisticated to express predictions. The fact of having included many monitoring variables constituted a point of advantage since it has been possible to determine which of the EVM metrics better fit the explanation of $CEAC$ variance. In line with this consideration, the primary goal of the author will be to propose to the company under examination a replacement of the already in-use $CEAC$ Revise Estimate traditional formula with the fitted linear models determined from the analysis. It can be highlighted that, especially in the early stage of the projects, when EVM data are scarce, the proposed predictions might elaborate better outcomes and enhance the level of forecasting.

Having had the possibility to focus the attentions on the most important variables associated with the $CEAC$, there is the chance to dismiss the common belief in the context of project management that the sole $CPI\ and\ SPI$ are the crucial performance metrics able to satisfy the remaining BAC adjustment in order to make forecasts. The weighted sum combination of the models' variables and their parameters estimate associated with the final cost might be diverse and not necessarily involving, for instance, the CPI whose behavior, in this analysis and many others, has been confirmed to be ambiguous and lacking predictive quality to explain the variance. Therefore, it can be said that not all the indicators are reliable and project managers should handle them with caution while monitoring is applied. The proposed framework has been able to also demonstrate this implication. Furthermore, the large influence of schedule and resource factors have been exhibited, since these performance indicators, either in term of index or variance, have been chosen by the LASSO procedure and confirmed by the multiple linear regression results. This underlined how being within the planned time and correctly estimating the effort distribution along the baseline are two fundamental aspects to diminish the final expenses. Lastly, the AC was confirmed, as hypothesized by the PMO, to be play a crucial role in statistical forecasting. ES concept was also included, conversely verified to have no association with the dependent variable.

The findings can constitute a base to be considered for application to a large spectrum of programme and portfolio types in various business environments, better if related to information technology and digital services, and participating in evolving the EVM analysis through statistics. Linea regression ensures a balanced trade-off between accuracy, variance, and easiness to use, as this study has demonstrated in line with already existing literature review and project management practices that attempt to improve project monitoring techniques and project performance.

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