POLITECNICO DI TORINO

MSc in Engineering and Management



Schedule Pressure Factor

A correction Factor for estimating the Final Project Duration

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Chapter 1

Introduction

1.1 Problem existence

Meeting deadlines is one of the most common and critical challenges in the management of construction and engineering projects. Several empirical studies show that most projects are completed later than planned, causing significant consequences in terms of additional costs, contractual penalties, and loss of value for the organizations involved.

Earned Value Management (EVM) is currently the most widely used quantitative framework for monitoring and controlling project performance. It integrates cost, progress and schedule into a coherent system of metrics and indices, providing the project manager with both a snapshot of current progress and a forecast of the final duration and cost. However, this formulation has a structural limit well documented in the literature: when a project approaches its deadline, the Schedule Performance Index (SPI) tends to converge to 1, regardless of the actual accumulated delay. As result, completion estimates derived from the SPI become progressively less reliable in the final stages of the project, precisely when the need for proper control is at its apex.

1.2 Problem importance

A wide range of stakeholders are aware of this issue. A more accurate estimate of Time Estimate at Completion (TEAC) enables project managers to prompt take corrective action. Reallocating resources, accelerating the schedule or revising the sequence of activities can have a significant impact on the final result. A reliable forecast of the delivery dates reduce uncertainty in strategic planning and minimizes contractual risks for customers and investors. For researchers in the project management field, comprehension and modeling of planning pressure represents a significant step beyond, connecting the behavioral dynamics with the quantitative metrics of project control.

The problem takes on particular relevance in contexts where projects experience cumulative delays and where the approaching deadline induces forced acceleration effects. In these scenarios, standard EVM models tend to systematically underestimate the final duration, generating optimistic estimates that do not reflect the actual project completion trajectory.

1.3 Old and state-of-the-art literature recap

Earned Value Analysis (EVA) has revolutionized project management by overcoming the limitations of traditional cost-budget accounting. Formalized by the U.S. Department of Energy in the 1980s and subsequently standardized by the PMI (2016), EVA introduces an integrated approach that combines costs, schedule, and performance. The quantification of the actual value of the performed work is the fundamental principle and added value of this frameworks.

The scientific literature has progressively improved the predictive capabilities of Earned Value Management, focusing on three key areas. First, improvements in estimation capabilities were driven by Anbari's framework (Anbari, 2003), which introduced a systematic approach to Estimate at Completion (EAC) based on multiple scenarios to consider the uncertainty of projects. At the same time, Vandevoorde and Vanhoucke (2006) highlighted the limitations of traditional indicators such as SPI, demonstrating how the adoption of Earned Schedule (ES) ensures greater accuracy in predicting the final project duration. Finally, regarding data accuracy, Chen (Chen, 2014) proposed to mitigate forecasting biases by applying Grey Modeling, derived from

Deng's (Deng, 1989) AGO technique, to Planned Value, a methodology that allows for refining the reliability of observed trends.

Today, research is based on a holistic approach: EVM is no longer merely an accounting reporting tool, but a complex predictive system that must balance advanced mathematical models with an understanding of the physical and motivational limitations of the resources involved in operations.

1.4 Gap

Despite significant methodological advances that have led Earned Value Management to evolve from a simple accounting tool into a sophisticated predictive framework, the existing literature still contains substantial gaps in the integration of behavioral dynamics into forecasting formulas. In particular, current EVM and Earned Schedule (ES) models are based on the assumption that current performance indices remain constant until project completion, ignoring the acceleration or deterioration of productivity induced by approaching deadlines.

Furthermore, there is a clear imbalance in academic focus, historically skewed toward estimating the final cost (EAC) at the expense of the final project duration (TEAC), even though schedule delays often represent the greatest concern for stakeholders. The lack of studies that propose and validate a parametric correction factor, such as a Schedule Pressure Factor, open new prospectives for researches.

1.5 Objectives

This thesis aims to improve the accuracy of completion estimates projects by defining and calibrating a Schedule Pressure Factor (SPF) as a corrective factor for the TEAC derived from the Earned Schedule. Specifically, the objectives are:

1. Defining the SPF as a normalized indicator of deadline pressure, reflecting the growing proximity to the deadline and the reduced capacity for recovery;

2. Calibrating the SPF parameters using historical project data, optimizing them to minimize the error between the estimated final duration and the actual duration;
3. Validating the model on real datasets, demonstrating that the inclusion of the SPF as a corrective factor statistically improves the accuracy of duration estimates compared to TEAC based on standard EVM.

The leading questions of this research are:

- To what extent do standard EVM formulas underestimate the final duration of projects?
- Is it possible to define an SPF pressure factor that, when applied to TEAC, reduces significantly this underestimation?

1.6 Structure

This thesis is organized as follows. Chapter 1 introduced the research problem, its practical significance, the existing gaps in behavioral project management literature, and the primary objectives of developing a Schedule Pressure Factor (SPF). Chapter 2 reviews the conceptual foundations of Earned Value Management (EVM) and Earned Schedule (ES), advanced forecasting models, and the psychological frameworks surrounding deadline pressure on construction sites. Chapter 3 describes describes the quantitative research framework, the Ghent University project dataset, the data transformation steps, and the mathematical formulation and optimization algorithms used to calibrate the parametric SPF model. Chapter 4 provides the results of the model validation process, presenting out-of-sample error reductions, Wilcoxon significance tests, and a detailed temporal-bin analysis of error distribution across the project lifecycle. Chapter 5 discusses the results, highlighting their theoretical and practical implications/the contribution to the theory and practice. Lastly, Chapter 6 summarizes the study, outlines its (de)limitations and suggests possible streams of future research.

Chapter 2

Literature Review

2.1 Earned Value Management: conceptual foundations and metrics

Earned Value Management (EVM) is a project control method that integrates the dimensions of scope, cost, and time into a coherent system of quantitative metrics (Project Management Institute, 2016). Unlike a simple comparison of actual cost and budget, which provides no information on the work actually performed (De Marco, 2018), EVM assigns a monetary value to each unit of work completed, allowing for a simultaneous assessment of cost and progress performance.

The framework is based on three fundamental parameters:

- BCWS (Budgeted Cost of Work Scheduled), also known as Planned Value (PV): planned cost of the work that was supposed to be completed by a certain deadline;
- BCWP (Budgeted Cost of Work Performed), also known as Earned Value (EV): the budgeted value of the work really completed up to that point;
- ACWP (Actual Cost of Work Performed), also known as Actual Cost (AC): the actual cost incurred to perform the completed work.

These three measures are used to derive the variance and efficiency indicators:

$$CV = EV - AC \quad \text{Cost Variance} \tag{2.1}$$

$$SV = EV - PV \quad \text{Schedule Variance} \tag{2.2}$$

$$CPI = \frac{EV}{AC} \quad \text{Cost Performance Index} \tag{2.3}$$

$$SPI = \frac{EV}{PV} \quad \text{Schedule Performance Index} \tag{2.4}$$

A CPI or SPI greater than 1 indicates better-than-expected cost or schedule performance, respectively; values less than 1 indicate cost overruns or delays (De Marco, 2018).

EVM also allows to estimate the final project cost (Estimate at Completion, EAC) and the completion date (Time Estimate at Completion, TEAC). In particular:

$$EAC_{optimistic} = BAC - CV \quad \text{future performance aligned with the budget} \tag{2.5}$$

$$EAC_{revised} = \frac{BAC}{CPI} \quad \text{future performance is expected to track with past performance} \tag{2.6}$$

$$TEAC_{original} = AT + \frac{(BAC - EV)(PD - AT)}{BAC - PV} \tag{2.7}$$

$$TEAC_{revised} = \frac{PD}{CPI} \quad \text{assuming that SPI remains constant} \tag{2.8}$$

A critical limitation of the traditional SPI is its tendency to converge to a value of 1 as the project nears completion. This phenomenon is determined by the very structure of the metric: when 100% of the work is complete, $EV = BAC = PV$, so $SPI = 1$ regardless of the actual lead or delay. Consequently, SPI and the duration estimates derived become progressively less informative in the final stages of the project [(Lipke, 2003); (De Marco, 2018)].

2.2 Earned Schedule: going beyond the SPI limits

To address the issue of the SPI converging to 1, Lipke (Lipke, 2003) introduced the concept of the Earned Schedule (ES). The ES converts progress in monetary terms (EV) into a time dimension by projecting the current EV value onto the PV curve and identifying the point in the plan at which that value could be earned. Formally, the ES is defined as:

$$ES(x) = C(x) + \frac{EV(x) - PV_c}{PV_{c+1} - PV_c} \tag{2.9}$$

where c denotes the number of periods during which the EV exceeds the PV. The derived time-based metrics are:

$$SV_t = ES - AT \quad \text{Schedule variance per unit of time} \tag{2.10}$$

$$SPI_t = \frac{ES}{AT} \quad \text{time based Schedule Performance Index} \tag{2.11}$$

By design, the SPI(t) does not converge to 1 at the end of the project but reflects the actual delay even in the final phases. The estimate of the final duration based on the Earned Schedule is:

$$TEAC_{ES} = \frac{PD}{SPI_t} \tag{2.12}$$

Subsequent studies [(Lipke, 2005); (Vandevoorde & Vanhoucke, 2006)] have experimentally validated the superiority of ES over traditional SPI for predicting final duration. It shows SPI(t) as a more stable and accurate indicator throughout the project lifecycle. Despite these advances, even estimates based on SPI(t) remain systematically optimistic when the project is behind schedule and nearing the deadline, as they do not incorporate the effect of deadline pressure on future performance.

2.3 Advanced forecasting models based on EVM

The evolution of estimation techniques has followed two main paths: the optimization of existing linear models and the introduction of nonlinear growth models. Regarding linearity, a

significant contribution came from Chen (Chen, 2014), who proposed an innovative approach to increase the accuracy of EVM forecasts through a transformation of PV, EV, and AC data. By utilizing the AGO (Accumulated Generating Operation) technique from Grey Modeling (Deng, 1989), Chen introduces a specific transformation formula:

$$PC_j^i(t)^{t*ln} = t * ln[PC_j^i(t)] \tag{2.13}$$

where $PC_j^i(t)$ represents the percentage of completion of PV, EV or AC at time t. The effectiveness of this method has been empirically confirmed on a sample of 131 projects, where the transformation significantly improved the correlation between the core variables, leading to a 13% reduction in MAPE for EV and a 19.93% reduction for AC.

However, the assumption that project progress follows a linear trend has often been questioned, as it does not reflect the operational reality in which most projects follow an S-curve (De Marco, 2018). To overcome this limitation, the literature explored the application of nonlinear growth models, such as logistic functions or the Gompertz model, which are better able to describe the lifecycle of costs and timelines: slow during the initial phase, accelerating in the middle, and slowing down again in the closing phases. In this regard, (Narbaev & De Marco, 2014) integrated these models with the Earned Schedule, demonstrating that the S-curve is superior in capturing the natural variations in pace typical of construction projects.

Nevertheless, these nonlinear methods more closely reflect the reality of engineering projects in theory, it remains a gap between research and professional practice. International standards and management software continue to favor linear estimates; a choice dictated not only by ease of application but also by the argument that the additional margin of precision offered by complex models is sometimes modest compared to the effort required for their implementation (Christensen et al., 1995).

2.4 SPF: Schedule Pressure Factor

Schedule pressure is defined as the pressure felt by individuals or work teams to complete their tasks within a specified timeframe (Nepal et al., 2006). In the construction industry, it typically

arises when a project is behind schedule and the site manager decides to speed up operations, or when the client imposes tighter deadlines to bring the product to market sooner. The relationship between time pressure and work performance is described by Yerkes-Dodson's Law (Wickens & Hollands, 2000): the curve is shaped like an inverted U, with optimal performance occurring at an intermediate level of pressure, as shown in Figure 2.1. Too little pressure leads to a lack of urgency and low efficiency; excessive pressure generates stress, disorganized work, compromised quality standards, and a loss of motivation, with clear negative effects on productivity.

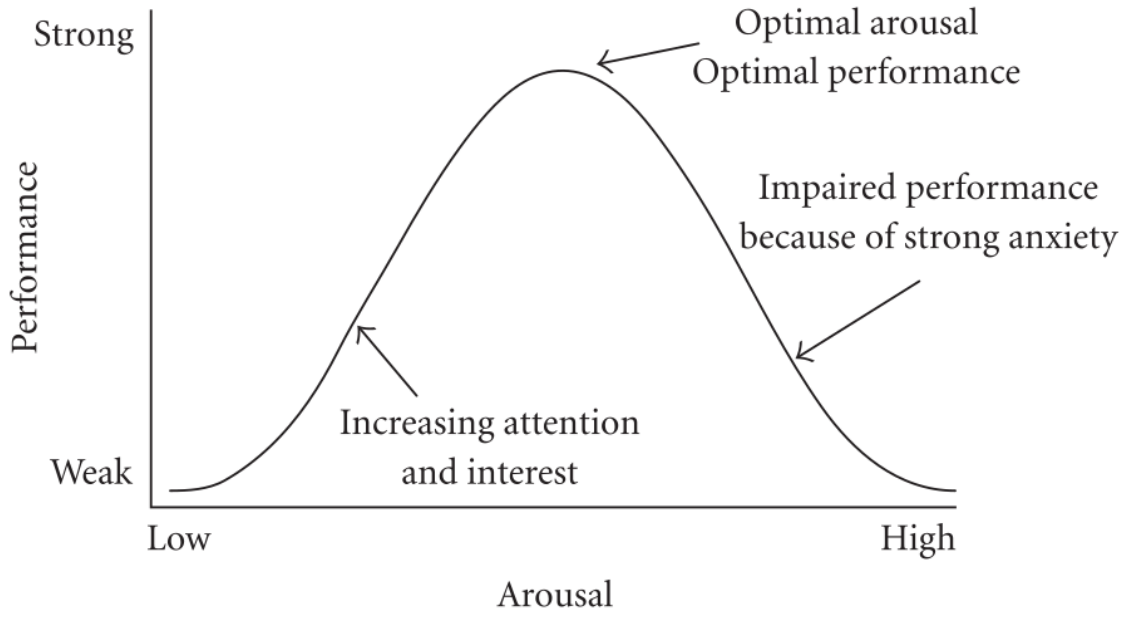


Figure 2.1: Hebbian version of the Yerkes–Dodson law.

. In Nepal, Park and Son (Nepal et al., 2006) translated this psychological framework into a causal model for construction sites, identifying the following mechanisms through which excessive pressure impairs performance:

1. Out-of-sequence work: Forced acceleration leads to performing tasks before prerequisites are completed, increasing rework;
2. Execution errors: selective use of available information leads to unintentional mistakes;
3. Cutting corners: workers deliberately choose to compromise on quality to meet deadlines;
4. Loss of motivation: when a deadline is perceived as unachievable, motivation at work

drops dramatically.

All these factors contribute to an increase in rework, which reduces overall productivity and exacerbates delays in a negative feedback loop. The findings of Nepal et al. (Nepal et al., 2006) have direct implications for EVM forecasting models. If deadline pressure increases the likelihood of rework and reduces actual productivity, then duration estimates derived from SPI(t), which project current performance unchanged into the future, will be systematically optimistic in the final stages of the project. Especially, when AT approaches PD (the planned time), scheduling pressure increases rapidly, but SPI(t) captures only the accumulated historical performance, not the expected deterioration. The inclusion of an SPF as a corrective factor for TEAC aims to fill this gap by adjusting the final duration estimate to account for the predictable deterioration in performance in the final stages.

Nepal et al. (Nepal et al., 2006) identify four main strategies for minimizing the negative effects of planning pressure:

1. Realistic planning of activities, with timelines tailored to available resources;
2. Intrinsic and extrinsic motivation of workers, including the setting of achievable short-term goals;
3. Proactive planning and anticipation of disruptions through constant monitoring of the construction site;
4. Effective coordination and communication among all project stakeholders, including sub-contractors and suppliers.

These strategies do not eliminate the phenomenon of schedule pressure, but they do mitigate its negative effects, suggesting that a forecasting model that accounts for such pressure is more robust than one that ignores it.

2.5 Summary and scope of the research

In summary, the literature review highlights how the most widely used methodologies for predicting project duration, as standard EVM and Earned Schedule, systematically overlook behavioral dynamics related to deadline pressure. This shortcoming appears significant when one

considers that scheduling pressure is a real and measurable phenomenon which, as empirically demonstrated by Nepal et al. (Nepal et al., 2006) in the construction sector, negatively impacts productivity precisely in the final stages of the project lifecycle. Even the most advanced contributions, including Chen's (Chen, 2014) approach, while optimizing forecast accuracy through data transformation, remain primarily focused on costs and physical progress, without explicitly integrating time pressure as an explanatory variable for final duration.

This thesis sits at the intersection of these research strands, proposing and validating a Schedule Pressure Factor (SPF) conceived as a corrective factor for TEAC.

Chapter 3

Research Methodology

3.1 Research framework

The study adopts a quantitative approach based on the analysis of historical project data. The methodological design is structured as follows:

(i) the collection and preprocessing of a dataset of real projects with complete EVM data, serving as the common basis for the analysis;

(ii) the formulation of the SPF model and its subsequent numerical calibration, aimed at further refining its parameters to minimize prediction errors on a training sample;

(iii) the validation of the calibrated model on an independent test set to assess its predictive accuracy against both the initial formulation and the standard EVM baseline.

To address the identified research gap, the study develops a **Parametric Forecasting Approach**. This methodology follows an empirical optimization path where the SPF is defined as a parametric function of the $SPI(t)$ and the gap between elapsed time (AT) and Earned Schedule (ES).

Unlike traditional linear projections, this approach accounts for the non-linear dynamics of schedule pressure. The model's parameters are specifically calibrated and validated using a

training-and-test split (60/30 project distribution) to ensure statistical robustness and to evaluate the model's capability to generalize across different project contexts.

3.2 Dataset and data source

The data analyzed in this study were provided by Ghent University, through the contribution of the Operations Research & Scheduling research group, which collected and organized a dataset consisting of 203 real-world projects from various organizations (Vandevoorde & Vanhoucke, 2006). This database contains baseline planning data (activity network, resources, durations), risk analysis data, and project monitoring data (EVM and ES metrics). The data are provided in the form of a list of projects, each accompanied by a summary sheet and an Excel file that includes visualizations and assessments of schedule and cost performance. The data most relevant to this study include:

- Tracking values: periodic snapshots of project progress, containing EVM metrics (PV, EV, AC, ES, SPI, SPI(t), CPI) at each time point;
- Baseline schedule: initial project plan, with Budget at Completion (BAC) and Planned Duration (PD);
- Actual schedule: actual progress, including actual final duration (AD) and actual final cost.

The dataset received for this research includes 90 projects, selected based on criteria of data completeness and reliability: the presence of complete baseline data (BAC and PD), the availability of periodic tracking values, and the absence of inconsistencies in progress data (Francios, 2025). The 90 projects cover various types (construction, industrial plants, infrastructure) and sizes, with budgets ranging from a few hundred thousand to several million euros and planned durations from a few months to over two years.

3.3 Data transformation and variable derivation

The data processing phase was structured into three primary stages to ensure temporal consistency and establish a rigorous baseline for comparison.

First, a detailed Critical Path Method (CPM) analysis was conducted across all project tracking periods. This involved the identification of the Critical Path (CP) and the calculation of CP Drag for each status date. By analyzing the longitudinal evolution of these parameters, it was possible to capture the shifting constraints and schedule bottlenecks throughout the project lifecycle.

Second, a significant temporal normalization was performed to standardize the measurement of time. The original AT (Actual Time) values, which were initially recorded as simple chronological enumerations of tracking periods, were converted into workdays. This transformation was achieved by calculating the specific number of working days between consecutive status dates. To maintain dimensional consistency across the dataset, the Planned Duration (PD), Actual Duration (AD) and Earned Schedule (ES) were similarly rescaled into days. This conversion was essential to ensure that the forecasting models reflected real-world operational constraints rather than abstract reporting intervals.

Finally, the standard Earned Value Management (EVM) forecasting baseline was established. The estimated duration at completion was calculated using the Earned Schedule approach as follows:

$$TEAC_{EVM} = \frac{PD}{SPI(t)}$$

To evaluate the predictive performance of this traditional metric, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were computed by comparing the $TEAC_{EVM}$ forecasts against the final AD. These error metrics provide the necessary benchmark to assess the incremental accuracy gained through the introduction of the proposed Schedule Pressure Factor.

3.4 Development of a Forecasting Parametric Approach

This approach introduces the development of a parametric model designed to adjust estimates of the project's final duration. The goal is to overcome the rigidity of standard EVM's linear projections by incorporating a correction factor that accounts for changes in time pressure.

3.4.1 Definition of the SPF model

The *Schedule Pressure Factor* (SPF) is conceived as a multiplier applied to the traditional $TEAC_{EVM}$. The proposed formulation for the SPF is as follows:

$$SPF = \alpha \cdot SPI(t)^{\beta} \cdot \left(1 + \gamma \frac{AT - ES}{PD}\right) \tag{3.1}$$

Consequently, the corrected estimated final duration ($TEAC_{SPF}$) is defined as:

$$TEAC_{SPF} = TEAC_{EVM} \cdot SPF \tag{3.2}$$

The variables that make up the model, which can be measured at each tracking period, are:

- $SPI(t) = \frac{ES}{AT}$: Schedule Performance Index;
- AT: *Actual Time*;
- ES: *Earned Schedule*;
- PD: *Planned Duration*.

The parameters α, β, and γ represent the sensitivity coefficients of the model. While the functional form of the SPF establishes the theoretical relationship between performance, accumulated delay and schedule pressure, these parameters allow for a data-driven refinement. In the following sections, it will be demonstrated how this structure provides an immediate improvement over standard estimates and how, through numerical optimization, the coefficients can be tuned to further maximize the model's predictive accuracy on a specific dataset.

The multiplicative structure of the SPF makes it possible to isolate two critical dimensions of temporal deviation:

Relative efficiency ($\alpha \cdot SPI(t)^{\beta}$) This first factor describes performance in terms of the rate of progress. The parameter α acts as a calibration constant for the baseline correction level under nominal conditions ($SPI(t) = 1$), while the exponent β models the nonlinearity of the system's response as efficiency varies.

Normalized absolute deviation ($1 + \gamma \frac{AT-ES}{PD}$) The second factor captures the accumulated delay in absolute terms. Unlike ratio indices such as $SPI(t)$, which may lose information about the magnitude of the delay in projects of different scales, the difference $(AT - ES)$ directly expresses the "lost" time. Normalization with respect to PD ensures that this information is proportional to the project's size, allowing us to distinguish, given the same performance index, the structural impact of a delay on projects of varying durations.

Intrinsic scale normalization It is worth noting that the normalization of time-based metrics with respect to PD is structurally inherent to the entire SPF formulation. In the relative efficiency component, explicitly normalizing both ES and AT by PD cancels out within the ratio, since $SPI(t) = \frac{ES/PD}{AT/PD} = \frac{ES}{AT}$. Conversely, in the absolute deviation component, this normalization by PD is explicitly embedded within the fraction $\frac{AT-ES}{PD}$. Consequently, all time-dependent inputs are naturally standardized relative to the project's planned duration, ensuring dimensional consistency and scale invariance across projects of different sizes without requiring pre-processing data scaling.

3.4.2 Behavior of the SPF

To understand the dynamic behavior of the SPF, we analyze the sensitivity of the function with respect to the independent variables ES and AT, using the product rule to calculate partial derivatives. We omit the analysis with respect to PD because, since the baseline duration is fixed at the start of the project, it does not constitute a dynamic variable during the monitoring and control phases.

Sensitivity with respect to the $SPI(t)$ index

If we consider the direct impact of the performance index while keeping the absolute lag component constant, we obtain:

$$\frac{\partial SPF}{\partial SPI(t)} = \alpha\beta \cdot SPI(t)^{\beta-1} \cdot \left(1 + \gamma\frac{AT - ES}{PD}\right) \tag{3.3}$$

This expression highlights how the model's responsiveness is strongly dependent on the value of the parameter β, which governs the elasticity of the forecast with respect to fluctuations in current efficiency.

Substituting $SPI(t) = \frac{ES}{AT}$, the explicit form of the SPF is:

$$SPF(ES, AT) = \alpha\left(\frac{ES}{AT}\right)^{\beta}\left[1 + \frac{\gamma}{PD}(AT - ES)\right] \tag{3.4}$$

Sensitivity with respect to the Earned Schedule (ES)

The partial derivative with respect to ES indicates how the adjustment factor varies as work progresses. Applying the product rule and factoring out $(\frac{ES}{AT})^{\beta-1}$, we obtain:

$$\frac{\partial SPF}{\partial ES} = \alpha\left(\frac{ES}{AT}\right)^{\beta}\left[\frac{\beta}{ES}\left(1 + \gamma\frac{AT - ES}{PD}\right) - \frac{\gamma}{PD}\right] \tag{3.5}$$

A negative value of this derivative suggests that an increase in actual progress (ES) tends to reduce the magnitude of the SPF correction, reflecting a recovery in the project's health.

Sensitivity with respect to Actual Time (AT)

The partial derivative with respect to AT expresses the impact of the passage of time alone on the forecast model. Applying the product rule and factoring out the common term $(\frac{ES}{AT})^{\beta}$, we obtain:

$$\frac{\partial SPF}{\partial AT} = \alpha\left(\frac{ES}{AT}\right)^{\beta}\left[-\frac{\beta}{AT}\left(1 + \gamma\frac{AT - ES}{PD}\right) + \frac{\gamma}{PD}\right] \tag{3.6}$$

This derivative allows us to model the increase in time-to-maturity pressure as time passes without a corresponding advance in the Earned Schedule.

3.4.3 Model calibration and parameter estimation

The calibration phase of the SPF model aims to determine the set of parameters (α, β, γ) that minimizes the discrepancy between the predictions provided by the framework and the actual project data. The objective function, the spatial constraints imposed, and the algorithmic procedure adopted are described below.

Objective function The calibration was guided by minimizing the *Mean Absolute Error* (MAE) between the model estimates and the actual final duration of the projects (AD):

$$\mathcal{L}(\alpha, \beta, \gamma) = \frac{1}{N} \sum_{i=1}^{N} |TEAC_{SPF,i} - AD_i| \tag{3.7}$$

where AD_i represents the final *Actual Duration* of the project corresponding to the i-th observation, and N denotes the total number of observations in the training sample.

The choice of MAE, preferred over metrics such as *Root Mean Squared Error* (RMSE) or *Mean Absolute Percentage Error* (MAPE), is driven by its superior robustness to *outliers*. While RMSE penalizes large errors quadratically, making the optimization excessively sensitive to individual outliers that could distort the parameter estimates, MAE ensures a linear influence of deviations. Compared to MAPE, MAE also avoids numerical instabilities arising from values close to zero and does not introduce systematic biases toward underestimation. Finally, the MAE provides a measure directly expressed in time units (days), ensuring immediate operational interpretability of the results.

Parameter constraints To ensure the numerical stability of the optimization process and preserve the physical consistency of the model, the following admissible intervals (*box constraints*) have been defined:

$$\alpha \in [-5.0, 5.0], \quad \beta \in [-3.0, 3.0], \quad \gamma \in [-3.0, 3.0] \tag{3.8}$$

- **Parameter α (Global scaling factor):** It acts proportionally on the $TEAC_{EVM}$ estimate. Negative values have been allowed to enable the algorithm to freely explore the solution space, although the range has been limited to ± 5 to avoid implausible projections that would compromise the model's interpretability.

- **Parameter β (Exponent of SPI_t):** Adjusts the sensitivity of the correction factor with respect to schedule efficiency. Given the lower bound of SPI_t at 0.01 (set during preprocessing), the interval $[-3, 3]$ appears suitable for capturing monotonic relationships between performance and correction, while preventing uncontrollable numerical amplifications.

- **Parameter γ (Normalized delay weight):** It governs the impact of the deviation $(AT - ES)$ relative to the PD. Limiting $|gamma| \leq 3$ prevents the absolute delay term from excessively dominating the relative efficiency component, reducing the risk of *overfitting* on projects characterized by extreme delays.

Optimization algorithm The search for the optimal solution was conducted using a two-stage approach, combining global optimization and local refinement techniques:

1. **First stage - Differential Evolution (DE):** Since this is a potentially non-convex problem and given the non-differentiability of the MAE function, a stochastic evolutionary algorithm was adopted. DE is particularly effective at exploring large regions of the parameter space while avoiding convergence to local minima. The configuration includes a population of 20 individuals, a mutation factor between 0.5 and 1.5, and a recombination rate of 0.7.

2. **Second stage - L-BFGS-B:** The optimal point identified by the DE was used as *input* for local refinement using the *Limited-memory Broyden–Fletcher–Goldfarb–Shanno* algorithm with boundary constraints. This quasi-Newtonian method allows for convergence with millimeter precision to the local minimum of the selected region.

Computational implementation The entire calibration workflow and error-minimization routines were computationally implemented in Python, relying on the scientific computing functionality provided by the `scipy.optimize` module (specifically `differential_evolution` and `minimize`). To ensure full reproducibility of the results, the source code developed for preprocessing, objective function evaluation, and two-stage optimization is provided in Appendix A.

Dataset and validation strategy The methodological framework utilized a total dataset of 90 projects. Calibration was performed on a *training set* of 60 projects, while the remaining 30 were used as a *test set* to verify the model's generalization ability on data not seen during optimization. Finally, the overall performance metrics were aggregated across the entire dataset (90 projects) to provide a comprehensive assessment of the predictive robustness of the proposed SPF formula.

Chapter 4

Validation of the Schedule Pressure Factor (SPF) Model

4.1 Introduction to the validation framework

Assessing the predictive effectiveness of a new indicator requires a rigorous methodological approach capable of comparing estimated values with actual observed outcomes, while also quantifying the informational gain achieved over existing methods. This chapter presents the validation procedure adopted for the Schedule Pressure Factor (SPF) model, with the objective of verifying its ability to improve the estimation of Time Estimate at Completion (TEAC) compared to the standard Earned Value Management (EVM) formulation.

The validation framework is structured into four complementary and progressively more demanding levels:

i. the definition of the error metrics used to evaluate predictive accuracy;

ii. the assessment of the actual improvement achieved through a comparison between the baseline EVM model and the SPF model, distinguishing between training and test sets;

iii. the verification of the statistical significance of the observed improvement through non-parametric tests;

iv. the analysis of the temporal distribution of prediction errors throughout the project life-cycle, in order to identify the phases in which the contribution of the SPF factor becomes most relevant.

4.2 Definition of error metrics

Let $TEAC_{EVM}^{(i,t)}$ and $TEAC_{SPF}^{(i,t)}$ denote the TEAC estimates generated respectively by the EVM and SPF models for project i at tracking period t, while AD_i represents the actual duration of project i. The squared and absolute errors at the individual tracking period level are defined as follows:

$$err_{(i,t)}^{EVM} = \frac{(TEAC_{(i,t)}^{EVM} - AD_i^2)}{PD_i^2} \tag{4.1}$$

$$err_{(i,t)}^{SPF} = \frac{(TEAC_{(i,t)}^{SPF} - AD_i^2)}{PD_i^2} \tag{4.2}$$

$$|err_{(i,t)}^{EVM}| = \frac{|TEAC_{(i,t)}^{EVM} - AD_i|}{PD_i} \tag{4.3}$$

$$|err_{(i,t)}^{SPF}| = \frac{|TEAC_{(i,t)}^{SPF} - AD_i|}{PD_i} \tag{4.4}$$

To ensure comparability across projects with diverse durations and varying reporting frequencies, the absolute errors were normalized by the Planned Duration (PD). This scaling eliminates the influence of project scale on the aggregate performance metrics.

Starting from these elementary errors, two aggregate project-level metrics are computed by considering all available tracking periods.

$$RMSE_i = \sqrt{\frac{1}{T_i}\sum_{t=1}^{T_i} err_{(i,t)}} \quad \text{Root Mean Square Error (RMSE) per project i} \tag{4.5}$$

$$MAE_i = \frac{1}{T_i}\sum_{t=1}^{T_i} |err_{(i,t)}| \quad \text{Mean Absolute Error (MAE) per project i} \tag{4.6}$$

RMSE assigns greater weight to large errors due to its quadratic formulation, making it particularly sensitive to outliers. MAE, on the other hand, provides a more robust and immediately

interpretable measure expressed directly in time units. Using both metrics jointly allows for a more comprehensive and balanced assessment of predictive accuracy.

4.3 Parameter calibration outcomes

The parameter estimation procedure described in Chapter 3 was executed on the training set (comprising 60 projects) using the two-stage optimization pipeline combining Differential Evolution and L-BFGS-B local refinement. The objective was to minimize the Mean Absolute Error (MAE) between the estimated $TEAC_{SPF}$ and the actual duration (AD).

The resulting optimal parameter values $(\alpha^*, \beta^*, \gamma^*)$ obtained from the calibration phase are summarized in Table 4.1.

Parameter	**Symbol**	**Optimal Value**
Global scaling factor	α	1,076589
$SPI(t)$ sensitivity exponent	β	0,955078
Normalized delay weight	γ	0,716469

Table 4.1: Optimal parameter values for the SPF model derived from the training set.

The empirical values obtained through the optimization process provide physical insight into the behavior of the Schedule Pressure Factor across the project portfolio:

- **Global scaling factor (α = 1,076589):** Adjusts the baseline level of the forecast under nominal conditions, fine-tuning the proportional relationship between $TEAC_{EVM}$ and $TEAC_{SPF}$.
- **Efficiency exponent (β = 0,955078):** Governs the non-linear responsiveness of the model to efficiency fluctuations measured by $SPI(t)$, determining how heavily past schedule performance impacts final duration estimates.
- **Delay weight (γ = 0,716469):** Modulates the impact of the normalized absolute delay $(AT - ES)/PD$, confirming that absolute temporal deviations carry substantial explanatory power regarding final time overruns.

These calibrated parameters establish the specific numerical configuration of the parameterized SPF model, which is subsequently evaluated out-of-sample in the following section.

4.4 Out-of-sample evaluation and measuring the improvement in accuracy

The parameters introduced by the SPF formulation were estimated through an optimization process performed on a training set, consisting of a subset of the overall dataset selected to be representative of the distribution of project types and time horizons included in the data. The remaining portion of the dataset constitutes the test set, on which the model is evaluated without any further adjustments.

This hold-out approach allows the model to be evaluated for generalizability, namely its accuracy on observations that were not used during calibration, thus reducing the risk of overfitting. The improvement observed on the test set, although expectedly smaller than that achieved on the training set, confirms that the predictive gain is genuine and not merely an artifact of parameter optimization.

The training/test split was performed at the project level rather than at the individual tracking-period level, in order to preserve the independence of observations and avoid temporal leakage between the two subsets.

The overall improvement achieved by the SPF model relative to the EVM baseline is quantified through two percentage improvement indices, computed by aggregating average values across the dataset.

The percentage improvement in MSE is defined as:

$$\Delta\text{MSE} = \frac{\overline{err}^{EVM} - \overline{err}^{SPF}}{\overline{err}^{EVM}} \tag{4.7}$$

where $\overline{err}$ denotes the average MSE across the entire dataset. It is important to note that this formulation measures the relative improvement in Mean Squared Error (MSE), rather than

directly in RMSE. The corresponding RMSE improvement would be:

$$\Delta\text{RMSE} = 1 - \sqrt{1 - \Delta\text{MSE}} \tag{4.8}$$

which is systematically smaller and should therefore be reported separately.

Similarly, the percentage improvement in MAE is defined as:

$$\Delta\text{MAE} = \frac{|\overline{err}^{EVM}| - |\overline{err}^{SPF}|}{|\overline{err}^{EVM}|} \tag{4.9}$$

where $|\overline{err}|$ represents the average MAE across the entire dataset.

Positive values for both indices indicate that the SPF model produces estimates that are, on average, more accurate than those generated by the reference EVM model. The results are shown in the Table 4.2 below:

Dataset	$\sqrt{\overline{\text{err}}^{\text{EVM}}}$	$\sqrt{\overline{\text{err}}^{\text{SPF}}}$	**Δ**RMSE	$\lvert\overline{\text{err}}^{\text{EVM}}\rvert$	$\lvert\overline{\text{err}}^{\text{SPF}}\rvert$	**Δ**MAE
Training set	1,31	0,18	86%	0,24	0,11	52%
Test set	0,64	0,17	73%	0,27	0,11	60%

Table 4.2: Percentage improvement of ΔRMSE and ΔMAE between Training set and Test set.

Similarly, Table 4.3 shows the improvement between the parameterized and non-parameterized models. As expected, the parameterized model shows greater improvement.

Model	$\sqrt{\overline{\text{err}}^{\text{EVM}}}$	$\sqrt{\overline{\text{err}}^{\text{SPF}}}$	**Δ**RMSE	$\lvert\overline{\text{err}}^{\text{EVM}}\rvert$	$\lvert\overline{\text{err}}^{\text{SPF}}\rvert$	**Δ**MAE
Parameterized model	1,12	0,18	84%	0,25	0,11	55%
Non-parameterized model	1,12	0,20	82%	0,25	0,13	49%

Table 4.3: Percentage improvement of ΔRMSE and ΔMAE between the parameterized and non-parameterized models.

4.5 Statistical significance assessment: Wilcoxon Test

A simple comparison of average errors is not sufficient to rule out the possibility that the observed improvement is due to sampling variability. For this reason, the Wilcoxon signed-rank

test is employed. This non-parametric paired test does not require the assumption of normally distributed errors, which is an assumption that is rarely satisfied in real-world project datasets.

The test is applied to the pairs ($RMSE_i^{EVM}$, $RMSE_i^{SPF}$) computed for each project in the test set. The unit of analysis is the individual project rather than the single tracking period, ensuring independence among observations: tracking periods belonging to the same project are inherently correlated and therefore cannot be treated as separate observations for statistical testing purposes.

The null hypothesis states that the distribution of differences $d_i = RMSE_i^{EVM} - RMSE_i^{SPF}$ is symmetric around zero, meaning that the two models exhibit equal median accuracy. The alternative hypothesis assumes that SPF systematically produces lower errors ($d_i < 0$).

The results obtained are summarized in Table 4.4 below:

Metric	$\mathbf{W^+}$	$\mathbf{W^-}$	**W**	**z**	**p-value**
RMSE	39	426	39	-3.98	$p < 0.001$
MAE	62	403	62	-3.51	$p < 0.001$

Table 4.4: Results of the Wilcoxon test for the Test Set using parameterized SPF model

As can be seen in Table 4.5, similarly, the test was applied to compare the entire data set between the EVM model and the non-parameterized SPF model and the following results were obtained:

Metric	$\mathbf{W^+}$	$\mathbf{W^-}$	**W**	**z**	**p-value**
RMSE	562	3523	562	-5.98	$p < 0.001$
MAE	723	3362	723	-5.33	$p < 0.001$

Table 4.5: Results of the Wilcoxon test for the Entire Set using non-parameterized SPF model

The negative sign of the test statistic confirms that the differences tend to be negative, indicating that the SPF model systematically produces lower errors than the EVM model. The p-values, which are well below the significance threshold for both metrics, demonstrate that the observed improvement is statistically significant and unlikely to be attributable to random variation.

4.6 Temporal analysis of error throughout the project lifecycle

A further level of analysis concerns the temporal distribution of prediction errors across the different phases of the project lifecycle. Since the projects included in the dataset exhibit heterogeneous planned durations, a direct comparison based on absolute tracking periods would be misleading. To address this issue, a normalization based on the ratio

$$T_{progress} = \frac{AT}{PD} \tag{4.10}$$

is adopted, where AT is the elapsed Actual Time and PD is the Planned Duration. This allows project progress to be represented on a common dimensionless scale within the interval [0,1).

To enable aggregation and graphical comparison of errors, the continuous values of $T_{progress}$ were discretized into 10 bins of width 0.10, centered at 0.05, 0.15, 0.25, ..., 0.95.

Each tracking period was assigned to the corresponding bin through the following formula:

$$T_{bin} = 0.1 \cdot \left\lceil \frac{T_{progress} - 0.05}{0.1} \right\rceil + 0.05 \tag{4.11}$$

where $\lceil \cdot \rceil$ denotes the ceiling function to the nearest upper multiple of 0.10.

This mechanism ensures that each value is associated with the center of the immediately higher bin. For example, $T_{progress} = 0.08$ is assigned to the bin centered at 0.15, while $T_{progress} = 0.22$ is assigned to the bin centered at 0.25. The bins cover the domain through mutually exclusive intervals of uniform width.

The analysis is restricted to the interval [0, 0.95], excluding the final phase immediately preceding the planned deadline, where the limited number of tracking periods would make average statistics less reliable and also where efforts to complete the project within the planned duration are now largely ineffective.

For each bin, the average error is computed as the mean of the errors associated with all tracking

periods belonging to that temporal interval, regardless of the originating project:

$$\overline{err}(b) = \frac{1}{S(b)} \sum_{(i,t) \in S(b)} err(i,t) \tag{4.12}$$

where $S(b)$ denotes the set of tracking periods such that $T_{bin} = b$.

The graphical comparison between the curves $|\overline{err}^{SPF}(b)|$ with $|\overline{err}^{EVM}(b)|$ makes it possible to visually identify the phases of the project in which the SPF factor provides the most significant predictive contribution. In particular, the advantage of the SPF model is expected to emerge primarily during the initial and intermediate phases of the project, where schedule pressure intensifies and the regression of SPI(t) toward unity, a phenomenon already documented in the literature, progressively reduces the discriminating power of standard EVM metrics.

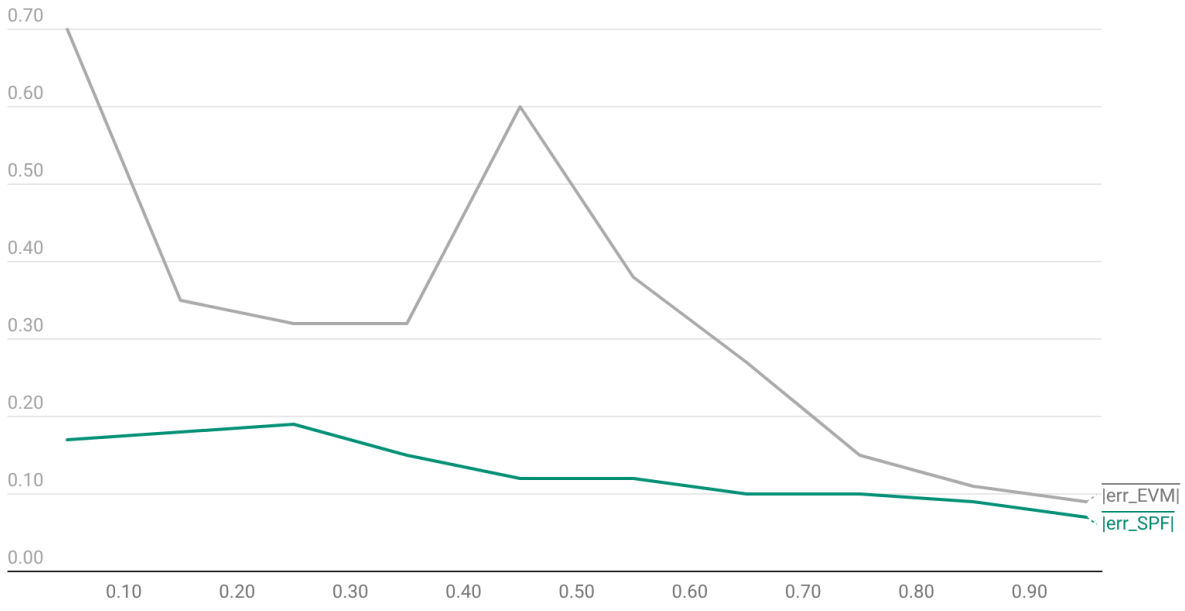


Figure 4.1: $|\overline{err}^{SPF}|$ vs $|\overline{err}^{EVM}|$ in the parameterized model.

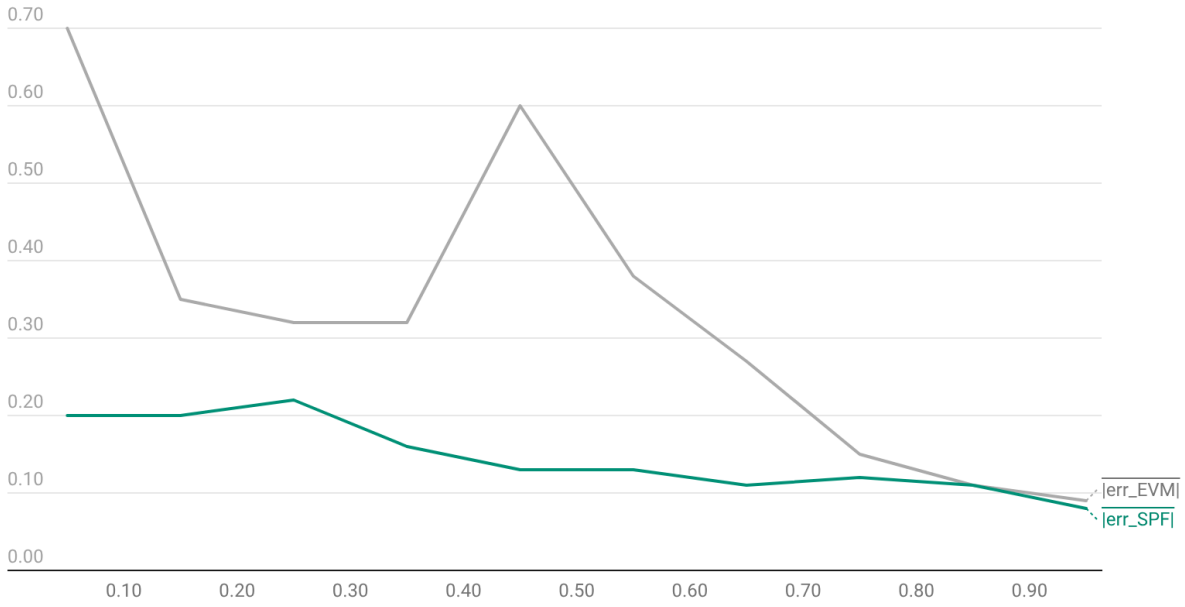


Figure 4.2: $|\overline{err}^{SPF}|$ vs $|\overline{err}^{EVM}|$ in the non-parameterized model.

To provide a more granular assessment of the model's reliability, the following figures illustrate the distribution of prediction errors using quartile analysis. By comparing the median and the interquartile ranges (Q_1 to Q_3) of the proposed SPF approach against the standard EVM baseline, we can evaluate not only the central tendency of the forecast accuracy but also the consistency of the results across the project lifecycle. This visualization highlights the dispersion of errors, providing insight into the model's robustness and its ability to mitigate extreme forecasting deviations compared to the traditional EVM method.

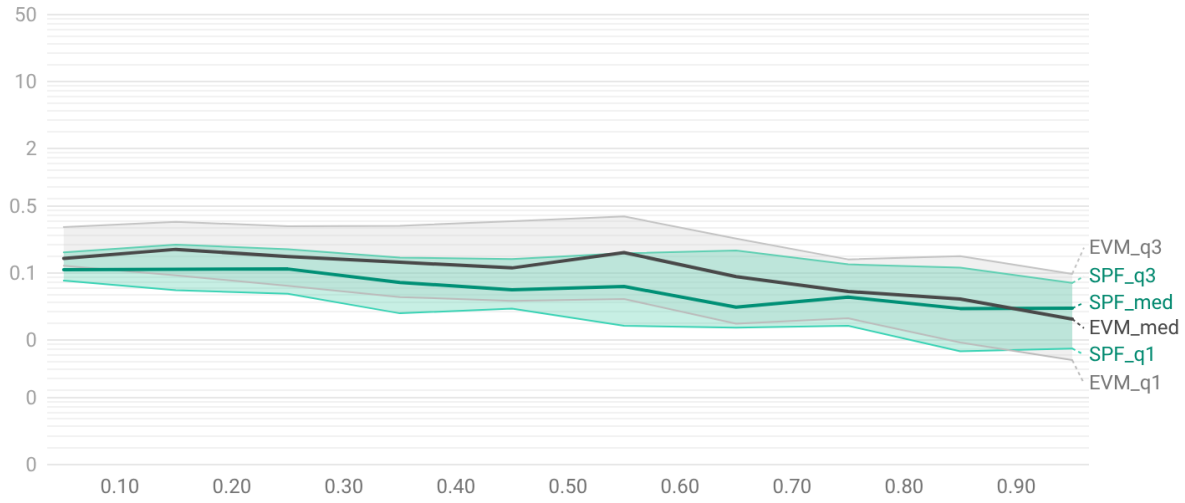


Figure 4.3: Comparison of mediana and interquartile range (q_1-q_3) for $|err^{SPF}|$ vs $|err^{EVM}|$ in the parameterized model.

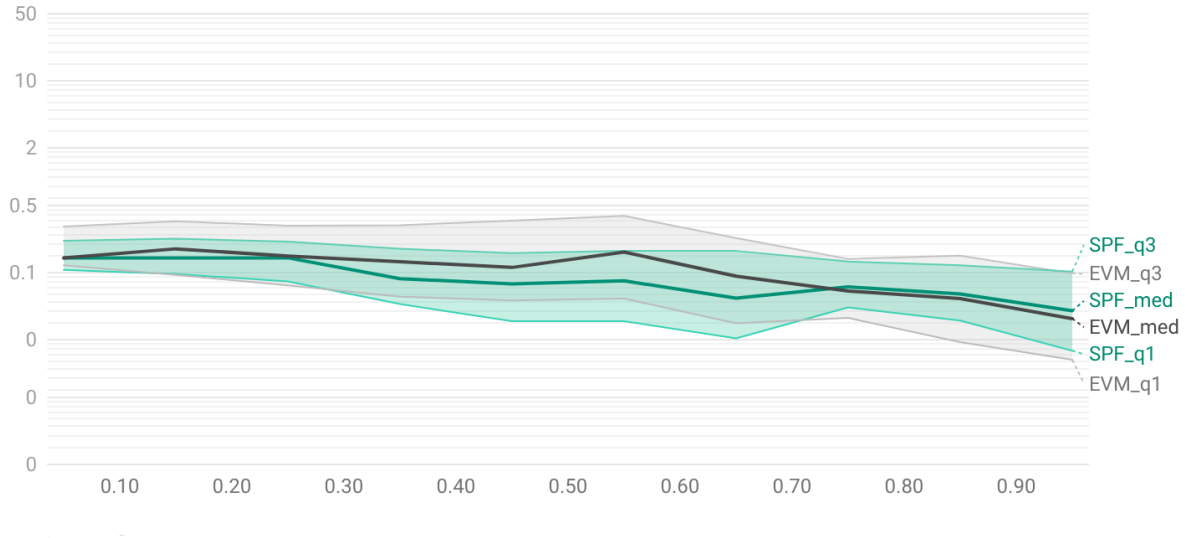


Figure 4.4: Comparison of mediana and interquartile range (q_1-q_3) for $|err^{SPF}|$ vs $|err^{EVM}|$ in the non-parameterized model.

The joint analysis of the error distributions highlights distinct temporal dynamics and provides deep insight into the behavior of both model configurations across the project lifecycle.

In the parameterized model scenario, the SPF maintains a remarkably stable and consistently lower error trajectory compared to the traditional EVM baseline. As shown in Figures 4.1

and 4.3, the EVM exhibits severe inaccuracy during early execution ($T_{\text{progress}} < 0.20$) and suffers from a major error spike centered around $T_{\text{progress}} = 0.45$, where the mean absolute error reaches nearly 0.60. In contrast, the parameterized SPF effectively suppresses this mid-project volatility, keeping the mean absolute error bounded below 0.18. The quartile analysis (Figure 4.3) further demonstrates that SPF_{med} remains systematically below EVM_{med} throughout the majority of the project duration ($0.05 \leq T_{\text{progress}} \leq 0.80$). Additionally, the interquartile range (q_1-q_3) for the SPF is substantially narrower during the initial and intermediate phases, highlighting a drastic reduction in forecast dispersion. Only in the closing stages ($T_{\text{progress}} > 0.80$) do the two models converge, as the mathematical properties of Earned Schedule naturally force traditional EVM metrics toward the actual duration near completion.

In the non-parameterized model context (Figures 4.2 and 4.4), the SPF demonstrates a similar ability to smooth out structural EVM deficiencies without requiring contextual parameter tuning. During the early stages ($T_{\text{progress}} \leq 0.20$), the median errors of both models are closely aligned. However, across the critical intermediate lifecycle interval ($0.25 \leq T_{\text{progress}} \leq 0.70$), the SPF clearly outperforms the EVM by eliminating the prominent $T_{\text{progress}} = 0.45$ error peak and maintaining a significantly lower median error alongside a tighter q_1-q_3 uncertainty band. Toward the project deadline ($T_{\text{progress}} > 0.75$), EVM_{med} slightly drops below SPF_{med}, while SPF_{q3} exhibits a minor relative rise at $T_{\text{progress}} = 0.95$. Overall, these results confirm that even in its generic, non-calibrated formulation, the SPF provides superior predictive stability during the operational core of the project lifecycle.

Note: The y-axis employs a logarithmic scale to compress the wide variance in error magnitudes (heteroscedasticity). This allows for a clear visualization of the model's precision across all projects, preventing large-scale errors from visually dominating the data distribution.

4.7 Discussion of results and limitations of the analysis

The overall validation results, presented in the figures and tables of the previous sections, show that the SPF model achieves a consistent improvement over the EVM baseline in terms of both MSE and MAE. This improvement is confirmed on the test set with strong statistical significance ($p < 0.001$ for both metrics) and remains robust even when comparing SPF on the test set

against EVM evaluated on the full dataset. The temporal-bin analysis further highlights that the improvement is not uniformly distributed throughout the project lifecycle, but is concentrated in the intermediate phases where schedule pressure becomes particularly critical.

Some limitations of the present analysis should nevertheless be acknowledged explicitly. First, the robustness of the results depends on the representativeness of the dataset: sector-specific characteristics or excessive homogeneity of the sample may limit the generalizability of the conclusions to different project environments. Second, the hold-out procedure is inherently sensitive to the specific training-set selection. Third, the temporal-bin analysis entails a loss of individual information due to the aggregation of tracking periods and the observed patterns may partially reflect structural heterogeneity within the sample, such as the uneven distribution of project types across different values of $T_{progress}$, rather than intrinsic properties of the model itself.

These limitations do not undermine the main conclusions of the study. Rather, they suggest several directions for future research, including: replication of the analysis on datasets from different application domains, exploration of alternative functional forms for the SPF factor and the integration of contextual project variables (such as project size, complexity and industry sector) into the parameter calibration process.

Chapter 5

Discussion

5.1 Discussion of results

The main purpose of this research is: evaluate whether the introduction of an explicit indicator of time pressure, termed the Schedule Pressure Factor (SPF), could improve the accuracy of forecasts regarding the final duration of projects compared to traditional approaches based on Earned Value Management (EVM). The experimental results validate this hypothesis, showing how the introduction of the SPF into the forecasting model leads to a statistically significant improvement in predictive performance.

The empirical analysis reveals a substantial reduction in both Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) compared to baseline EVM models. On the out-of-sample test set, the model achieved a 73% improvement in RMSE and a 60% improvement in MAE (compared to 86% and 52% on the training set). Furthermore, during the evaluation of the entire dataset, the parameterized SPF model demonstrated an 84% improvement in RMSE and a 55% improvement in MAE. These metrics align closely with the 82% (RMSE) and 49% (MAE) gains observed in the non-parameterized version. This proximity indicates that while parameter calibration provides a tangible gain in precision, the fundamental SPF formulation possesses inherent structural robustness, returning high predictive accuracy even without extensive fine-tuning.

From a methodological perspective, these findings validate the core hypothesis of this research:

relying solely on physical and economic progress metrics is insufficient to fully capture the temporal dynamics of project execution. Two projects may exhibit identical values for Earned Value, Planned Value, and Earned Schedule, yet operate under vastly different time pressure conditions due to contractual deadlines. The Schedule Pressure Factor fills this informational gap by substantially modeling the non-linear relationship between accumulated delay, remaining time margin, and schedule efficiency.

A key insight from the experimental analysis concerns the dynamic behavior of prediction errors across the project lifecycle. Rather than showing uniform performance gains, the temporal analysis reveals that the SPF's primary advantage lies in suppressing the severe volatility and error spikes characteristic of traditional EVM during the intermediate phases of execution ($0.25 \leq T_{\text{progress}} \leq 0.70$). Around the midpoint of project duration ($T_{\text{progress}} \approx 0.45$), where traditional EVM exhibits a major loss of accuracy, the SPF effectively stabilizes forecasts by accounting for schedule pressure. In the closing stages ($T_{\text{progress}} > 0.80$), the performance of both models naturally converges as Earned Schedule metrics stabilize near project completion.

Additionally, the quartile analysis (Q_1, median, Q_3) confirms that the SPF does not merely lower average error metrics, but narrows the interquartile range and mitigates extreme deviations. This stability aligns with observations in project management literature regarding how management control functions. As noted by Chen, while traditional research has focused primarily on refining forecasting algorithms using existing variables, introducing new explanatory features capable of modeling organizational constraints provides a more effective path to forecast enhancement.

The statistical validity of these performance gains is confirmed by the Wilcoxon signed-rank test ($p < 0.001$ for both RMSE and MAE across all evaluated configurations). The non-parametric analysis confirms that the observed error reductions reflect a systematic superiority of the SPF model rather than random sampling variations. Overall, the evidence demonstrates that the Schedule Pressure Factor complements established EVM metrics by explicitly modeling a critical managerial dimension that traditional progress indicators overlook.

5.2 Theoretical implications

The results achieved in this research offer several points for reflection when examined through a theoretical lens, the insights gained from this study contribute significantly to the evolution of studies on project forecasting and, more generally, on project monitoring and control methodologies. In particular, this thesis contributes significantly by introducing a new explanatory variable that quantifies time pressure: a well-known phenomenon in project management practice that is rarely modeled in forecasting tools.

As discussed in Chapter 2, the evolution of Earned Value Management over the past few decades has followed a trajectory focused primarily on refining forecasting techniques through the definition of new performance indicators and increasingly sophisticated mathematical models. The introduction of the Earned Schedule by Lipke and subsequent developments proposed by Vanhoucke and colleagues represented a fundamental step in this direction, making it possible to overcome some of the limitations of traditional EVM in estimating project duration. Similarly, numerous subsequent contributions have proposed different statistical formulations or regression models with the aim of increasing the accuracy of time forecasts.

In this context, this study takes a different approach. Rather than directly modifying the forecasting algorithm or redefining traditional performance indicators, this research proposes to enrich the available data set by introducing the Schedule Pressure Factor. This methodological choice stems from the consideration that the quality of a predictive model depends not only on the technique used to make the forecast, but also on the ability of the input variables to effectively represent the phenomena that influence the project's progress.

From this perspective, this research builds on the observations made by Chen, who points out that most studies on Earned Value Management have focused on improving forecasting procedures while leaving the informational content of the variables under consideration essentially unchanged. The author emphasizes the need to identify new elements capable of enhancing the predictive power of the models, noting that the accuracy of estimates depends not only on the mathematical formulation adopted but also on the quality of the available information. The results obtained in this thesis confirm this insight, demonstrating that the introduction of an additional variable can significantly improve the model's performance without altering the

fundamental structure of the forecasting process.

Another theoretical contribution concerns the mathematical formalization of schedule pressure. In the project management literature, the concept of schedule pressure is frequently invoked to describe the operational conditions that characterize the final phases of a project, in which the reduced time margin available tends to increase the decision-making burden, the need to reallocate resources, and the likelihood of delays. However, in most cases, this phenomenon is addressed primarily in qualitative terms or considered a consequence of the project's progress, without being explicitly integrated into quantitative forecasting models.

The definition of the Schedule Pressure Factor proposed in this study therefore represents an attempt to fill this gap, translating a predominantly theoretical concept into a numerical indicator that can be directly used within forecasting models. The decision to describe the increase in pressure using a nonlinear function is further justified both by empirical observations on project behavior and by the organizational dynamics that characterize progress monitoring. The progressively accelerating increase in the SPF reflects the reduction in recovery capacity that accompanies the approach of the planned deadline, a behavior consistent with what is observed in professional practice.

In terms of mathematical modeling, the capacity to calibrate the SPF's parameters offers a significant advantage. Experimental results show, in fact, that time pressure does not necessarily follow the same pattern across all projects, but can take on different characteristics depending on the industrial sector, organizational maturity, planning methods, and control practices adopted. Parameterizing the SPF thus makes it possible to transform a general indicator into a tool that can be adapted to different application contexts, introducing greater flexibility compared to approaches that use fixed formulations independent of the dataset's characteristics.

This observation suggests a broader reflection on the role of contextualization in project forecasting models. Many traditional approaches implicitly assume that the relationship between project progress and final duration is essentially uniform across different organizations. The results of this research, however, indicate that part of the observed variability in forecasting performance can be explained by the influence of organizational factors that alter how time pressure evolves over the project lifecycle. From this perspective, the SPF can be interpreted not only as a new predictive feature but also as a composite indicator of the organizational

response to the progressive reduction in available time.

Finally, this research helps bridge two lines of study that, while addressing complementary aspects of project management, have often been developed separately. On the one hand, the literature on Earned Value Management has focused primarily on the quantitative measurement of time and cost performance; on the other hand, studies on schedule pressure have examined the effects of time pressure on organizational behavior, productivity, and decision-making processes. The introduction of the Schedule Pressure Factor allows us to bridge these two perspectives by incorporating into a quantitative model a phenomenon typically analyzed from an organizational standpoint. In this sense, the theoretical contribution of this dissertation lies not only in improving the accuracy of forecasts but also in proposing a conceptual framework that integrates traditional progress measures with indicators capable of representing changes in the project's operational conditions.

Overall, the results therefore suggest that the integration of variables describing the management context may represent a promising direction for the development of future project forecasting models. Rather than focusing exclusively on progressively increasing the mathematical complexity of forecasting algorithms, this research highlights how a significant improvement in performance can result from enriching the informational content of the variables used, thereby fostering a more comprehensive representation of the dynamics that govern the evolution of projects.

5.3 Practical implications

In addition to the theoretical contributions discussed in the previous section, the results of this research have important practical implications for project management. The improvement in forecast accuracy achieved through the introduction of the Schedule Pressure Factor (SPF) is not merely a methodological advancement but can translate into concrete support for the decision-making processes involved in project monitoring and control.

One of the main challenges in project management concerns the timely identification of potential delays relative to the initial schedule. The ability to obtain more accurate forecasts of the final duration allows project managers to take proactive corrective actions to reduce the

risk that deviations will be identified only in the final stages of the project, when the scope for intervention is already limited. In this context, the introduction of the SPF provides additional information beyond traditional progress indicators, highlighting the intensity of the pressure exerted by the progressive reduction in available time.

In day-to-day operations, this predictive enhancement allows project managers to distinguish between two projects that, despite sharing similar EVM metrics, are experiencing vastly different levels of time pressure. A project in the final stages of execution with a high SPF value requires a different level of managerial attention than a project with the same level of progress but still far from its planned deadline. The Schedule Pressure Factor therefore helps contextualize the information provided by traditional metrics, enabling a more comprehensive assessment of the project's actual status.

This applicability is particularly relevant to periodic monitoring activities. As De Marco points out, project control does not consist solely of collecting data on progress, but above all in transforming that information into tools to support managerial decision-making. The goal of project control is, in fact, to enable timely interventions that keep the project aligned with its time, cost, and quality objectives. From this perspective, an indicator such as the SPF can enhance the project information system by providing a concise measure of time-related criticality that complements established performance indicators.

The use of the SPF can also support decisions regarding resource allocation. When a project enters phases characterized by increasing time pressure, the project manager is frequently called upon to evaluate actions such as increasing available resources, adjusting operational priorities, bringing forward certain activities, or revising the schedule. Having a quantitative measure of scheduling pressure can help make these decisions more objective, reducing reliance on purely qualitative assessments or the project manager's individual experience.

Another area of application concerns the operation of Project Management Offices (PMOs) and structures responsible for simultaneously overseeing multiple project initiatives. In organizations that manage project portfolios, available resources are generally limited and must be allocated among initiatives with varying levels of criticality. In such contexts, the SPF could serve as an additional prioritization criterion, making it possible to identify projects that, despite showing seemingly satisfactory progress indicators, are entering a phase in which mounting

time pressure increases the likelihood of significant delays.

The results of the pilot study also suggest that the SPF can be integrated into the monitoring dashboards already in use by many organizations. Since the indicator is calculated using information that is typically available in project control systems, its implementation does not require substantial changes to existing data collection processes. This represents a significant advantage over methodologies that require new measurement campaigns or the collection of data that is difficult to obtain during project execution.

The introduction of the SPF also aligns with the growing use of digital tools for project monitoring. Modern project management platforms, in fact, allow for the continuous updating of performance indicators and the automatic generation of management reports. In this context, the Schedule Pressure Factor could be calculated dynamically with each progress update, providing project managers with immediately available information on changes in time pressure. A graphical representation of the SPF's trend over time could also facilitate the identification of anomalous trends and support communication with stakeholders during reporting activities.

At an organizational level, a significant advantage stems from the ability to use the SPF as a complementary indicator in the historical analysis of completed projects. The parameter calibration proposed in this study highlights that time pressure can manifest differently depending on the organization's characteristics and the type of project. The availability of historical data therefore allows the model to be adapted to the company's specific operating procedures, fostering a gradual improvement in forecasting capabilities through a continuous learning process based on accumulated experience.

It is important to emphasize that the practical contribution of the SPF is not to replace the established tools of Earned Value Management or Earned Schedule, but rather to complement them. Traditional metrics continue to serve as the primary benchmark for measuring project performance, while the Schedule Pressure Factor adds a complementary perspective regarding the time-critical nature of the context in which that performance is observed. This integration is consistent with the evolution of project management practices, which are increasingly oriented toward multidimensional monitoring systems in which different metrics work together to provide a comprehensive picture of the project's status.

Ultimately, the results suggest that the proposed approach may prove particularly useful in projects characterized by high organizational complexity, strong interdependence among activities, and particularly tight contractual deadlines. In such contexts, even small deviations from the plan can have amplified effects on the final duration, making it particularly valuable to have forecasting tools capable of promptly detecting an increase in time pressure. Although further validation across different application contexts is necessary, the findings from this research indicate that the Schedule Pressure Factor is a promising indicator from both a methodological and an operational standpoint, offering project management professionals an additional tool to support more informed decisions and improve the effectiveness of project monitoring activities.

Chapter 6

Conclusions

6.1 Summary of contributions

This thesis started from a relatively simple but important observation: even though traditional project control techniques such as Earned Value Management (EVM) and Earned Schedule (ES) provide useful information about project progress, their ability to forecast the final project duration is not always consistent throughout the lifecycle. In particular, previous empirical evidence has shown that forecasting errors can become particularly substantial and volatile during the intermediate stages of a project. This is also the period in which reliable forecasts can be most valuable, since there is still enough time for project managers to take corrective action.

The purpose of this research was therefore not to replace existing forecasting approaches, but to complement them with information that is relevant to the way schedule pressure develops over time. To this end, the Schedule Pressure Factor (SPF) was introduced as a quantitative indicator of the increasing pressure experienced by a project as it approaches its planned completion date. The underlying idea is that the same level of delay or schedule inefficiency does not necessarily have the same meaning at different points in the project lifecycle. A delay occurring relatively early in a project may still be recoverable, while the same delay close to the planned completion date can have much more serious consequences.

Based on this idea, the SPF combines schedule efficiency, expressed through SPI_t, with the

normalized absolute delay $(AT - ES)/PD$. The proposed formulation was then calibrated through an automated optimization procedure based on Differential Evolution and L-BFGS-B. This made it possible to estimate the parameters of the model without changing the structure of the underlying EVM-based forecasting approach.

The empirical results provide strong evidence in favour of the proposed approach. When the parameterized SPF was used, the forecasting error was reduced by up to 84% in terms of RMSE and by 55% in terms of MAE compared with traditional EVM over the full dataset. More importantly, the improvement was not limited to the data used during model development. On the independent test set, the model still achieved reductions of 73% in RMSE and 60% in MAE. This is a meaningful result because it suggests that the improvement is not simply the consequence of fitting the model to the available observations, but that the SPF can also provide useful information when applied to projects that were not part of the calibration process.

The results obtained with the non-parameterized formulation are particularly interesting in this respect. Even without calibrating the parameters using historical project data, the SPF produced reductions of 82% in RMSE and 49% in MAE. The difference between the two formulations is relatively limited, suggesting that much of the effectiveness of the indicator comes from its underlying functional structure rather than exclusively from the estimated coefficients. From a practical perspective, this is encouraging because organizations that do not have sufficiently large or reliable historical datasets may still be able to benefit from the proposed approach.

The analysis of forecasting errors over the project lifecycle provides another important insight. The strongest improvements were observed during the intermediate phases of project execution, approximately within the range $0.25 \leq T_{\text{progress}} \leq 0.70$. In these stages, the traditional EVM forecasts showed considerable volatility and pronounced error peaks. The inclusion of the SPF substantially reduced this instability and produced more consistent estimates. This result is particularly relevant from a project management perspective. The value of a forecasting model is not only determined by how accurate it is at the end of a project, when the outcome is already largely known, but also by how reliably it can support decisions while there is still time to influence the final outcome.

The statistical analysis further supports these findings. The non-parametric Wilcoxon signed-rank tests resulted in p-values below 0.001, indicating that the observed improvements are

statistically significant and are unlikely to be explained by random differences between the forecasting methods.

Taken together, these findings suggest that schedule pressure represents a useful additional dimension for project duration forecasting. The SPF does not require a complete redesign of existing project control systems. Instead, it provides additional information that can be incorporated into an established forecasting framework. This also gives the indicator a practical interpretation: projects that appear similar in terms of percentage completion or schedule efficiency may nevertheless be in very different situations if their remaining time and accumulated delay are different. Making this distinction explicit may help project managers and Project Management Offices (PMOs) identify critical situations earlier and focus their attention where intervention is most needed.

6.2 Delimitations

As with any empirical study, the scope of this research was defined by a number of deliberate boundaries. The SPF was developed specifically for the prediction of final project duration, represented by $TEAC$. Other dimensions of project performance, such as cost, quality, and scope, were not directly considered. This choice allowed the analysis to remain focused on the relationship between schedule pressure and duration forecasting accuracy.

The proposed approach is also designed for execution-phase application. It assumes that a time baseline, represented by the planned duration PD, is already available. The SPF is therefore not intended to support the initial development of a project schedule or to determine whether the original baseline itself is realistic. Its purpose is instead to improve forecasting once the project is underway and actual performance data become available.

Finally, the empirical evaluation was carried out using a standardized dataset containing 90 projects. The dataset includes projects with different characteristics in terms of scale and sector, which provides some degree of diversity for the analysis. Nevertheless, the results are inevitably linked to the characteristics of the available sample. The findings should therefore be interpreted within this context, and their applicability to substantially different project environments should be investigated through further empirical validation.

6.3 Limitations

The results of this thesis should also be considered in light of several limitations.

The first concerns the calibration of the parameterized model. The estimated coefficients (α, β, γ) depend on the historical data used for calibration. This means that the quality of the calibration is necessarily related to how representative the available projects are of the projects to which the model will subsequently be applied. If an organization experiences significant changes in its project environment, management practices, technologies, or operating conditions, the previously estimated parameters may become less appropriate. In such situations, recalibration may be necessary.

A second limitation is linked to the aggregated nature of the SPF itself. The indicator captures schedule pressure through a mathematical formulation, but it does not attempt to explain why that pressure has emerged. In reality, increasing schedule pressure can result from many different causes, including resource constraints, technical difficulties, scope changes, procurement issues, or external disruptions. These factors may have very different managerial implications, even if they ultimately result in a similar level of schedule pressure. The current formulation does not distinguish explicitly between these causes.

A further limitation is that the model focuses on forecasting rather than on the managerial decisions that follow from the forecast. In a real project environment, an increase in schedule pressure may lead to actions such as reallocating resources, changing priorities, accepting additional costs, reducing scope, or introducing specific risk mitigation measures. These actions can subsequently affect project performance and, in turn, future forecasts. Such feedback mechanisms are not explicitly represented in the current model.

These limitations do not invalidate the results obtained in this study, but they define the context in which the SPF should currently be interpreted. In particular, the indicator should be viewed as an additional source of information for project control rather than as a complete representation of all the factors that determine project performance.

6.4 Future Research

The results obtained in this thesis suggest several possible directions for future research.

A first and important step would be to test the SPF on a wider range of projects and industries. The dataset considered in this study provides useful empirical evidence, but additional validation would help determine whether the observed improvements remain consistent in environments with substantially different project characteristics. Applications to software development, aerospace, large infrastructure projects, and other highly specialized domains could also reveal whether the sensitivity of the SPF parameters varies across industries.

Another interesting direction would be to investigate how the SPF could be combined with machine learning techniques. In the present study, the indicator is incorporated into a structured forecasting approach. Future work could instead use the SPF as one of several input features in machine learning or ensemble regression models. This would make it possible to explore whether interactions between schedule pressure and other project characteristics can provide additional improvements in forecasting accuracy.

The calibration process could also be made more adaptive. At present, the parameters are estimated using historical data, but project conditions can change as execution progresses. Future research could therefore investigate online calibration approaches capable of updating the SPF parameters as new observations become available. Bayesian updating, for example, could provide a way of progressively adapting the model while retaining information from previous projects. Such an approach could be particularly useful in organizations where project portfolios evolve over time.

Finally, the concept of schedule pressure could be extended beyond duration forecasting. Since schedule pressure can influence decisions involving resources, costs, risks, and scope, it could potentially become part of a broader multidimensional project performance framework. An integrated model combining schedule pressure with cost and risk indicators could provide a more complete picture of the overall condition of a project and support more informed managerial decisions.

6.5 Concluding remarks

The main contribution of this thesis is the introduction and empirical evaluation of the Schedule Pressure Factor as an additional dimension for project duration forecasting. The results show that explicitly considering the pressure associated with approaching the planned completion date can substantially improve the accuracy and stability of traditional EVM-based forecasts.

Perhaps the most relevant finding is not simply the magnitude of the overall error reduction, but where this improvement occurs. The SPF is particularly effective during the intermediate stages of project execution, when forecasting errors can be highly volatile but corrective action is still possible. In this sense, the proposed indicator addresses a practical problem in project management: providing more reliable information at a point in time when that information can still make a difference.

At the same time, the results suggest that the SPF can be introduced without fundamentally changing existing project control practices. It can be used as an additional indicator within a familiar forecasting framework, making the approach relatively straightforward to interpret and potentially easier to integrate into existing monitoring systems.

Overall, this research supports the idea that project duration forecasting can benefit from explicitly accounting for the changing pressure associated with time. Traditional performance indicators describe how a project is progressing, but they do not necessarily capture how critical a given level of performance becomes as the deadline approaches. The SPF was developed to address this gap.

The findings presented in this thesis therefore provide both an empirical contribution, through the demonstrated improvements in forecasting accuracy, and a conceptual contribution, by introducing schedule pressure as a distinct and measurable dimension of project performance. While further validation and development are still needed, the results indicate that this perspective has the potential to complement existing project control methods and to support earlier and more informed managerial intervention.

Appendix A

Python Code for Model Calibration

In this appendix, the Python implementation used for the preprocessing, objective function definition, and parameter optimization (combining Differential Evolution and L-BFGS-B) is reported.

Listing A.1: Python calibration script

```python
import warnings
import numpy as np
import pandas as pd
from scipy.optimize import minimize, differential_evolution
import os

warnings.filterwarnings("ignore")

# ---------------------------------------------
#  1. LOADING & PREPROCESSING
# ---------------------------------------------

def load_and_preprocess(filepath: str) -> pd.DataFrame:
    """Loads the file, cleans the data, and calculates necessary features."""
    df = pd.read_excel(filepath)

    # Normalize column names
    df.columns = [c.strip().lower().replace(" ", "_").replace("(", "").replace(")", "") for c
        in df.columns]

    print(f"[INFO] Dataset loaded: {df.shape[0]} rows, {df.shape[1]} columns.")
    print(f"[INFO] Unique projects: {df['code'].nunique()}")

    # Ground Truth: final_ad is the project's AD (constant per code)
    df["final_ad"] = df.groupby("code")["ad"].transform("max")
```

```
25
26      # Relative time progress
27      df["t_progress"] = df["at"] / df["pd"]
28
29      # Cleaning: replace infinities and NaNs
30      for col in ["spi_t", "cp_drag", "teac_evm", "t_progress"]:
31          df[col] = pd.to_numeric(df[col], errors="coerce")
32          df[col].replace([np.inf, -np.inf], np.nan, inplace=True)
33
34      rows_before = len(df)
35      df.dropna(subset=["spi_t", "cp_drag", "teac_evm", "t_progress", "final_ad"], inplace=True)
36      print(f"[INFO] Rows after NaN/Inf cleaning: {len(df)} (removed {rows_before - len(df)})")
37
38      # Clip outliers for numerical stability
39      df["spi_t"] = df["spi_t"].clip(lower=0.01)
40      df["cp_drag"] = df["cp_drag"].clip(lower=1)
41      df["t_progress"] = df["t_progress"].clip(lower=0.01, upper=5.0)
42
43      return df
44
45
46  # ---------------------------------------------
47  #  2. SPF FUNCTION & PREDICTION
48  # ---------------------------------------------
49
50  def calculate_spf(params, features):
51      """
52      SPF = a * SPI_t^b * (1 + c * (AT - ES) / PD)
53      params = [a, b, c]
54      """
55      a, b, c = params
56      spi_t   = features["spi_t"].values
57      at      = features["at"].values
58      es      = features["es"].values
59      pd_     = features["pd"].values
60
61      with np.errstate(all="ignore"):
62          delay_norm = np.where(pd_ != 0, (at - es) / pd_, 0.0)
63          spf = a * np.power(np.abs(spi_t), b) * (1.0 + c * delay_norm)
64          spf = np.where(np.isfinite(spf), spf, 1.0)
65
66      return spf
67
68  def predict_teac_spf(params: np.ndarray, df: pd.DataFrame) -> np.ndarray:
69      spf = calculate_spf(params, df)
70      return df["teac_evm"].values * spf
71
72
73  # ---------------------------------------------
```

```python
# ---------------------------------------------
#  3. OBJECTIVE FUNCTION
# ---------------------------------------------

def objective_mae(params: np.ndarray, df: pd.DataFrame) -> float:
    """MAE between teac_spf and final_ad."""
    pred = predict_teac_spf(params, df)
    residuals = pred - df["final_ad"].values
    if not np.all(np.isfinite(residuals)):
        return 1e12
    return np.mean(np.abs(residuals))


# ---------------------------------------------
#  4. OPTIMIZATION
# ---------------------------------------------

def optimize_spf(df: pd.DataFrame):
    """Performs optimization with Differential Evolution + L-BFGS-B refinement."""
    print("\n[OPTIMIZATION] Starting global search (Differential Evolution)...")

    bounds = [(-5.0, 5.0), (-3.0, 3.0), (-3.0, 3.0)]

    de_result = differential_evolution(
        func=objective_mae,
        bounds=bounds,
        args=(df,),
        seed=42,
        maxiter=500,
        tol=1e-8,
        popsize=20,
        mutation=(0.5, 1.5),
        recombination=0.7,
        polish=True,
        workers=1,
    )

    # Local refinement with L-BFGS-B
    print("[OPTIMIZATION] Local refinement (L-BFGS-B)...")
    lbfgs_result = minimize(
        fun=objective_mae,
        x0=de_result.x,
        args=(df,),
        method="L-BFGS-B",
        bounds=bounds,
        options={"maxiter": 2000, "ftol": 1e-12, "gtol": 1e-10},
    )

    best_params = lbfgs_result.x if lbfgs_result.fun < de_result.fun else de_result.x

```

```
    return best_params


# ---------------------------------------------
#  5. MAIN
# ---------------------------------------------

def main():
    # Define dataset directory (replace with local path)
    BASE_DIR = "path/to/project_directory"
    INPUT    = os.path.join(BASE_DIR, "SPF_Input - 60.xlsx")

    # 1. Preprocessing
    df = load_and_preprocess(INPUT)

    # 2. Optimization
    best_params = optimize_spf(df)

    # 3. Print final formula
    a, b, c = best_params
    print("\n" + "=" * 65)
    print("  OPTIMIZED SPF FORMULA:")
    print(f"SPF = {a:.6f} * SPI_t^{b:.6f} * (1 + {c:.6f} * (AT - ES) / PD)")
    print(f"  TEAC_SPF = TEAC_EVM x SPF")
    print("=" * 65)

    print("\n[DONE] Process completed successfully.")
    return best_params


if __name__ == "__main__":
    main()
```

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