UNIVERSITY OF SÃO PAULO

RODRIGO GOULART VOTTO

CONTROL CHARTS FOR PROJECT MONITORING: CONTRIBUTIONS TO THE STATISTICAL PROJECT CONTROL

São Paulo

2021

RODRIGO GOULART VOTTO

CONTROL CHARTS FOR PROJECT MONITORING: CONTRIBUTIONS TO THE STATISTICAL PROJECT CONTROL

Revised Version

Ph. D. Thesis presented to the Polytechnic School of University of São Paulo (USP) for the degree of Doctor of Science

Concentration area: Production Engineering

Advisors:
Profa. Dra. Linda Lee Ho
Prof. Dr. Fernando Tobal Berssaneti

São Paulo

2021

RODRIGO GOULART VOTTO

GRÁFICOS DE CONTROLE EM MONITORAMENTO DE PROJETOS: CONTRIBUIÇÕES NO CONTROLE ESTATÍSTICO DE PROJETO

Versão Corrigida

Tese apresentada à Escola Politécnica da Universidade de São Paulo (USP) para obtenção do título de Doutor em Ciências

Área de Concentração: Engenharia de Produção

Orientadores:
Profa. Dra. Linda Lee Ho
Prof. Dr. Fernando Tobal Berssaneti

São Paulo

2021

This copy was revised and changed in relation to the original version, under the sole responsibility of the author and with the consent of his supervisor.

São Paulo, January 22nd, 2021.

Este exemplar foi revisado e alterado em relação à versão original, sob responsabilidade única do autor e com a anuência de seu orientador.

São Paulo, 22 de janeiro, 2021.

Cataloging in the publication

Library and Documentation Service

University of São Paulo

VOTTO, RODRIGO GOULART
Control charts for project monitoring: contributions to the statistical project control / R.G. VOTTO -- São Paulo, 2020
76 p.

Tese (Doutorado) - Escola Politécnica da Universidade de São Paulo. Departamento de Engenharia de Produção.

1.GESTÃO DE PROJETOS 2. CONTROLE ESTATÍSTICO DO PROCESSO 3.SIMULAÇÃO I.Universidade de São Paulo. Escola Politécnica. Departamento de Engenharia de Produção II.t.

To my parents, my role models, who gave me life and guided me throughout it,
to my brother, sister, and friends, who showed me how to enjoy it,
to Clara, my love, who shares every moment of it with me, and
to my beloved daughter, Helena, who made life completely wonderful.

ACKNOLEDGMENTS

The completion of this thesis represents a great personal victory and the fulfillment of a dream. This work would not be possible without the support and contributions of a large number of people, some of them, I must name in the following lines.

I am grateful to my family, especially my parents, Romildo and Catarina, my Grandfather, Arceu Goulart, my dear Brother and Sister Junior and Rejane, for the life example, the everyday support, and the motivation to pursue all my dreams. To my Grandmother Santa (*in memoriam)*, for turning simple words into our family motto: "*Começar é de todos, continuar é dos fortes, concluir é dos heróis...*" (Unknown author). Such words have guided my decisions throughout my life.

To Clara, my love, for the patience, the understanding, and the unconditional support in all stages of my life, especially, during these challenging times. To my beloved daughter, Helena, who was born during this journey and, without any free will, had to share her father's time with this work.

To Professor Dra. Linda Lee Ho for her guidance, dedication, teachings, trust, and incredible support over the years. It was an honor and privilege to have the guidance and friendship of such a renowned professor. Her contribution and commitment to this work brought the theoretical foundation, the serenity and time pressure necessary to every research project. To Professor Dr. Fernando Berssaneti, for his orientation, friendship, and the long and necessary "out-of-the-office" discussion sections.

To all professors and staff of the Production Engineering Department of the Polytechnic School of the University of São Paulo (USP), in special to Lidia, for the great support, reminders, and push in every step.

To the company Voith Paper, to my leaders over these years (Hjalmar Fugmann, Flavio Silva, and Claudio Ramos), to my team and all the colleagues who supported me and contributed to the realization of this work.

Finally, I thank God for guiding my way, for giving me health and peace of mind to overcome challenges and open new doors whenever one closes.

AGRADECIMENTOS

A conclusão desta tese representa uma grande vitória pessoal e a concretização de mais um sonho. Este trabalho não seria possível sem o apoio e contribuição de um grande número de pessoas, algumas as quais eu não posso deixar de agradecer.

Agradeço a toda minha família, em especial aos meus pais Romildo e Catarina, o Vovô Arceu Goulart, meus queridos irmãos Junior e Rejane, meus heróis e pilares morais, pelo exemplo de vida, pelo apoio no dia a dia e pela motivação para perseguir todos os meus sonhos. Agradeço à Vovó Santa (*in memoriam*) por transformar simples palavras em nosso lema de família: "*Começar é de todos, continuar é dos fortes, concluir é dos heróis...*" (autor desconhecido). Tais palavras têm guiado minhas decisões durante toda minha vida.

À Clara, meu amor, pela paciência, compreensão e apoio incondicional em todas as etapas da minha vida, principalmente, nestes tempos desafiadores.

À minha querida filha Helena, que nasceu durante esta jornada e, sem qualquer livre arbítrio, teve que compartilhar o tempo do seu pai com este trabalho.

À Professora Dra. Linda Lee Ho por sua orientação, dedicação, ensinamentos e confiança ao longo dos anos. Foi uma honra e um privilégio contar com a orientação de tão renomada professora. Sua contribuição e comprometimento com este trabalho trouxeram a fundamentação teórica, a serenidade e a pressão de tempo necessárias a qualquer projeto de pesquisa. Ao Professor Dr. Fernando Berssaneti, pela orientação e pelas longas e necessárias sessões de discussão "fora do escritório".

A todos os professores e funcionários do Departamento de Engenharia de Produção da Escola Politécnica da Universidade de São Paulo (USP), em especial à Lídia, pelo grande apoio, lembretes e cobranças em todas as etapas do programa.

À empresa Voith Paper, aos meus líderes ao longo desses anos (Hjalmar Fugmann, Flavio Silva e Claudio Ramos), à minha equipe e a todos os colegas que me apoiaram e contribuíram para a realização deste trabalho.

Para finalizar, eu agradeço a Deus por guiar meus caminhos, por me dar saúde, serenidade e paz de espírito para superar os desafios e abrir novas portas sempre que uma se fecha.

“If you can't explain it simply, you don't understand it well enough”
Albert Einstein

“Veni, vidi, vici…”
Julius Caesar, general and consul of Rome, in a letter to the senate, around 47 BC, after achieving a quick victory at the Battle of Zela.

ABSTRACT

This thesis proposes a statistical project control approach to monitor the cost and duration performance of projects. The literature review on the application of statistical process control for project monitoring pointed towards the use of control charts with control limits based on simulated samples as a powerful method to set thresholds to distinguish between acceptable and not acceptable variation on the project performance. However, the existing literature on the use of such charts is still very incipient and was limited to the use of cost-based data to monitor exclusively the duration dimension of project performance.

Therefore, addressing the key theoretical gaps, the statistical project control approach proposed in this thesis brings four major contributions to the project management body of knowledge and to the statistical process control literature. First, the exclusive use of time-based data, from the recently proposed Earned Duration Management (EDM), to monitor the project duration performance using control charts with probability control limits. Second, the use of such control charts to monitor the cost performance of projects using Earned Value Management (EVM) observations. Third, the use of multivariate control charts to simultaneously monitor the duration and cost performance of projects. Finally, a decision-making process to set the control limits such that they enable the project team drilling down to lower project levels only when it is really necessary, avoiding investing time and effort to investigate false alarms.

This is a paper-based thesis and its outcomes are five papers. In this sense, this document brings the findings and methodological aspects of each publication as well as the integration among them to establish a holistic view on the proposed statistical project control approach.

The output of the research is a framework to build univariate and multivariate control charts to monitor the cost and duration performance of projects and a process to set the most appropriate probability control limits. Numerical examples were used to illustrate the use of the method on real-life construction projects and simulation experiments were performed to assess the performance of the proposed charts. The experiment results demonstrated that the proposed methods exhibit a good performance facilitating the interpretation of the actual deviations during the project execution, distinguishing between the common and special sources of variation.

KEYWORDS. Project Management; Statistical Process Control; Risk Analysis; Earned Value Management; Earned Duration Management; Simulation

RESUMO

Esta tese propõe uma abordagem de controle estatístico de projetos para monitorar o desempenho de custo e duração de projetos. A revisão da literatura sobre a aplicação de controle estatístico de processo para monitoramento de projetos indicou que a utilização de gráficos de controle com limites de controle baseados em amostras simuladas pode ser um método poderoso para distinguir variações aceitáveis e não aceitáveis de desempenho na execução de projetos. No entanto, a literatura existente sobre o uso de tais gráficos no gerenciamento de projetos ainda é muito incipiente e se limitava ao uso de indicadores baseados em custos para monitorar exclusivamente a dimensão da duração do desempenho dos projetos.

Portanto, identificadas as principais lacunas teóricas, a abordagem de controle estatístico de projetos proposta nesta tese traz quatro contribuições principais para o corpo de conhecimento de gerenciamento de projetos e para a literatura de controle estatístico de processos. Em primeiro lugar, o uso exclusivo de indicadores baseados no tempo, da metodologia proposta mais recentemente Earned Duration Management (EDM), para monitorar o desempenho da duração de projetos usando gráficos de controle com limites probabilísticos de controle. Em segundo lugar, o uso de tais gráficos de controle para monitorar o desempenho dos custos dos projetos, usando observações da metodologia Earned Value Management (EVM). Terceiro, o uso de gráficos de controle multivariados para monitorar simultaneamente o desempenho de duração e de custos de projetos. Finalmente, um processo de tomada de decisão para definir mais apropriadamente os limites de controle de forma que possibilitem à equipe do projeto investigar os detalhes de cada atividade do projeto apenas quando for realmente necessário, evitando investir tempo e esforço para investigar alarmes falsos.

Esta é uma tese em formato de coletânea de artigos e seu resultado está baseado em cinco artigos. Nesse sentido, este documento traz os achados e aspectos metodológicos de cada publicação, bem como a integração entre eles, para estabelecer uma visão holística sobre a abordagem de controle estatístico de projetos proposta.

O resultado da pesquisa é um modelo para construir gráficos de controle univariados e multivariados para monitorar o desempenho de custo e duração dos projetos e um processo de tomada de decisão para definir os limites probabilísticos de controle. Exemplos numéricos foram utilizados para ilustrar o uso do método em projetos de construção e de bens de capital e experimentos de simulação foram realizados para avaliar o desempenho dos gráficos propostos. Os resultados dos experimentos demonstraram que os métodos propostos apresentam um bom desempenho o que facilita a interpretação dos desvios reais durante a execução do projeto, distingue entre causas comuns de variação, que ocorrem quando o projeto está em controle estatístico, e causas especiais (assinaláveis) de variação, que devem ser interpretadas como evidências de um risco real de atraso ou desvio de custos do projeto.

Palavras-chave. Gerenciamento de projetos; Controle estatístico de processo; Análise de risco; *Earned Value Management*; *Earned Duration Management*; Simulação

LIST OF FIGURES

LIST OF TABLES

ABREVIATIONS

AC	Actual Cost
BAC	Budget at Completion
BPD	Baseline Planned Duration
CDF	Cumulative Probability Functions
CPI	Cost Performance Indicator
DPI	Duration Performance Index
ED	Earned Duration
EDI	Earned Duration Index
EDM	Earned Duration Management
EPC	Engineering, Procurement and Construction
ES	Earned Schedule
ESM	Earned Schedule Management
EV	Earned Value
EVM	Earned Value Management
LCL	Lower Control Limit
PV	Planned Value
PDF	Probability Distribution Function
SP	Serial-Parallel Indicator
SPC	Statistical Process Control
SPI	Schedule Performance Index
SPI(t)	Schedule Performance Index Based on Earned Schedule
TPI	Time Performance Index
TAD	Total Actual Duration
TED	Total Earned Duration
TPD	Total Planned Duration
UCL	Upper Control Limit
WBS	Work Breakdown Structure

SUMMARY

PART I – INTEGRATIVE THESIS OVERVIEW

1 INTRODUCTION

This thesis proposes a statistical project control approach to monitor the cost and duration performance of projects. In order to accomplish this objective, the research has followed a progressive approach, starting with the literature review on the evolution and trends on the application of statistical process control (SPC) for project monitoring and on the earned value methodologies used for project control.

The outcomes of this initial stage have pointed towards the key theoretical gaps in the literature and have driven the following steps of the research. The use of control charts with probability control limits based on simulated samples was identified as a powerful method to set thresholds to distinguish between acceptable and not acceptable variation on the project performance. However, the existing literature on the use of such control charts for project monitoring is still very incipient and it was limited to the use of cost-based data to exclusively monitor the duration dimension of project performance.

Therefore, addressing the main gaps, the statistical project control approach proposed in this thesis brings four major contributions to the SPC literature and to the project management (PM) body of knowledge. First, the exclusive use of time-based data, from the recently proposed Earned Duration Management (EDM), to monitor the project duration performance using control charts with probability control limits. Second, the use of such control charts to monitor the cost performance of projects using Earned Value Management (EVM) observations. Third, the use of multivariate control charts to simultaneously monitor the duration and cost performance of projects. Finally, the proposal of a decision-making process to set the most appropriate control limit width such that it enables the project team drilling down to lower project levels only when it is really necessary, avoiding investing time and effort to investigate false alarms.

This is a paper-based thesis and its outcomes are five papers. The three journal papers, that are the core of this study, cover each of the research specific objective in a comprehensive manner. Complementarily, two conference papers provided the bases of the literature review and supported the first research steps and objective. In this sense, this document brings the findings and methodological aspects of each publication as well as the integration among them to establish a holistic view on the proposed statistical project control approach.

The research proposed different solutions, univariate or multivariate approaches, to monitor the cost and duration performance of projects and a framework to set the most appropriated control limit width. Numerical examples were used to illustrate the use of the method on real-life construction projects, and simulation experiments were performed to assess the performance of the proposed charts. The experiment results demonstrated that the proposed methods exhibit a good performance facilitating the interpretation of the actual deviations during the project execution, distinguishing between the common and special sources of variation.

1.1 Research Problem and Justification

Project control aims to measure and evaluate the actual progress and the performance of a project by comparing it with a baseline scheduling, analyzing the eventual deviations, and taking necessary early actions to correct these deviations to ensure that the project is completed on time and within budget (Acebes et al., 2014; 2015; Hazir, 2015; Willems & Vanhoucke, 2015).

A widely used managerial methodology for project performance monitoring is the Earned Value Management (EVM), which integrates the cost and the schedule control in the same framework and provides performance indexes that enable the project teams to anticipate the cost overruns and the project delays (Pajares & López-Paredes, 2011; Colin & Vanhoucke, 2014; Khamooshi & Golafshani, 2014; Acebes et al., 2014; 2015). Initially, EVM focused mainly on costs. Afterwards, the attention has gradually shifted to the duration control partially due to the study of Lipke (2003), which introduced the concept of Earned Schedule Management (ESM), as an extension of EVM, to improve the monitoring of the actual project progress.

More recently, Khamooshi and Golafshani (2014) introduced the Earned Duration Management (EDM) to emphasize the duration dimension of projects and address some shortcomings of EVM and ESM caused by the use of cost-based metrics as proxies to assess the project duration performance (Vanhoucke et al., 2015; Votto et al., 2020a). Its foundation lies in the exclusive use of time-based data to generate the duration indicators (Vanhoucke et al., 2015; Ghanbari et al., 2017a).

Despite the great success of these methodologies, they often utilize intuitive thresholds based on the practical experience to distinguish between the acceptable and the not acceptable variations from the project baseline schedule, which was highlighted as one of the main shortcomings of EVM and its extensions (Colin & Vanhoucke, 2014; Colin & Vanhoucke, 2015a; Salehipour et al., 2016; Wauters & Vanhoucke, 2017). To overcome these problems, an active area of development in academic literature focused on the application of control charts to monitor project performance. These charts differentiate abnormal signals that indicate actual problems from normal signals that do not affect the project success (Bauch & Chung, 2001; Wang et al., 2006; Leu & Lin, 2008; Aliverdi et al., 2013; Colin & Vanhoucke, 2014, Colin et al., 2015; Băncescu, 2016; Salehipour et al., 2015; Hadian & Rahimifard, 2019; Votto et al., 2020a; 2020b).

Introduced by Shewhart in 1924, control charts have been widely applied to a variety of industries and processes (Montgomery, 2009). Traditionally, control charts have been used to monitor the stabilities of various parameters (such as the mean, the standard deviation, and the non-conforming fraction) of production processes over time. Recently, these charts were adopted to monitor the quality of services and determine if the spread of a particular disease reached an epidemic level; they were also utilized in public health surveillance and social networks (Votto et al. 2020a).

The primary problem for using the control charts for a project monitoring relates to the fact that it is associated with a repeatable and long term process to monitor the deviations from the normal progress as defined by the observed data. However, rather than an on-going process, the projects are defined as finite and unique endeavors that do not completely follow any repeatable process (Wang et al., 2006; Lipke et al., 2009; Colin & Vanhoucke, 2014; Vanhoucke, 2017).

Therefore, the appropriate setting of the thresholds for project control based on how the state of control is defined has been a target of fruitful discussions in the literature. Vanhoucke (2019) classified the thresholds for the project monitoring into three categories, the static, the analytical and the statistical control limits. Additionally, the control charts can be built in different ways depending on the samples of the progress data (Martens & Vanhoucke, 2017). First, the control limits can be calculated based on historical data either from the initial project phases or from similar projects (Bauch & Chung, 2001; Wang et al., 2006; Leu & Lin, 2008; Aliverdi et al., 2013; Băncescu, 2016; Salehipour et al., 2016). However, the concept of similarity among projects is often vague and questionable and has been target of several critics

(Colin & Vanhoucke, 2014; Vanhoucke, 2019; Votto et al, 2020a; 2020b). Alternatively, the probability control limits can be determined by simulated samples, based on the acceptable variation of each activity duration and cost (Colin & Vanhoucke, 2014; Votto et al., 2020a).

These probability control limits based on the simulated samples are argued to be the most powerful method, although the most complexity as well. To overcome the shortcoming of depending of historical data, it relies on more advanced statistical analysis and requires computerized methods to generate and analyze the simulated data and assume a shift from the project management by experience to a data driven management approach (Vanhoucke, 2019). Introduced by Colin and Vanhoucke (2014) these control charts with statistical thresholds based on a simulated sample were restricted to the project schedule monitoring using the cost based EVM and ESM performance indicators. To the best of the author's knowledge, the control charts with statistical thresholds based on simulated samples had never been used with the following objectives:

a) To monitor the duration performance of projects using a time based duration performance index (DPI), from EDM;
b) To monitor the cost performance of projects using the cost performance indicator (CPI), from EVM;
c) To simultaneously monitor the duration and the cost performance of projects;
d) Furthermore, there is no method in the literature to support the choice of the most appropriate control limit width for each project, depending on its targets and risk management decisions.

In this context, the need for having a more comprehensive statistical project control approach with control limits determined by simulated samples provides a rationale for this research. Its aims to answer the following question: *Can the use of control charts with probability control limits to monitor the duration and cost of projects improve the ability to distinguish between acceptable and not acceptable variations, and trigger appropriate actions when the observed variation in project's progress exceeds a certain predefined threshold?*

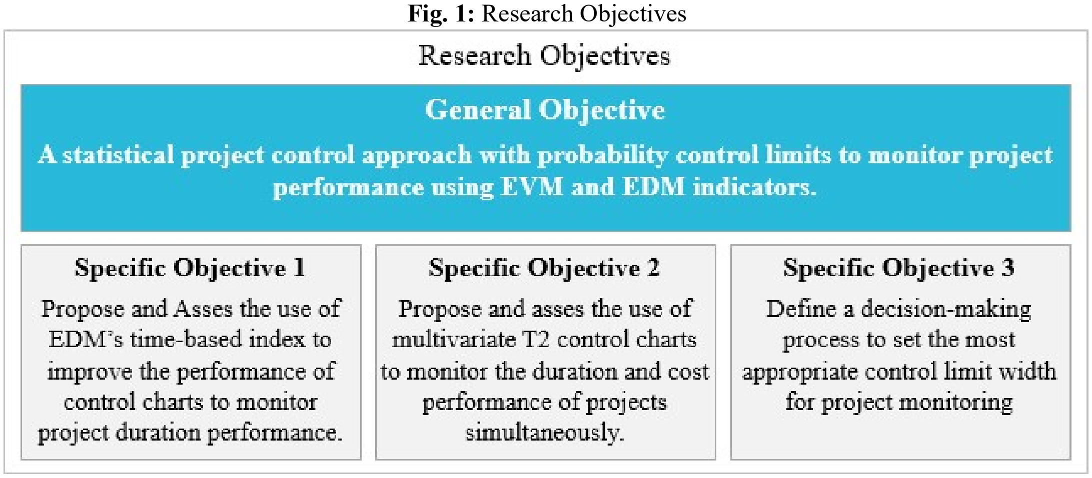
1.2 Research Objectives

Previous section highlighted the major gaps in the literature of the control chart for project monitoring and the research problem. In order to address such gaps and to answer the research question, the general objective of this thesis is: **A statistical project control approach with**

probability control limits to monitor the project performance using EVM and EDM indicators. This general objective is deployed into three specific objectives, depicted in Fig. 1.

1. Propose and asses the use of EDM's time-based index to improve the performance of control charts for the project duration monitoring.
2. Propose and asses the use of multivariate control charts to simultaneously monitor the duration and the cost performance of projects with control limits based on simulated samples.
3. Define a decision-making process to set the most appropriate control limit width for the project monitoring, such that it timely triggers corrective actions only when real deviations are identified and, simultaneously, reduces the effort in further investigations of false alarms.

Fig. 1: Research Objectives



Source: Figure developed by the author for this thesis

1.3 Thesis Structure

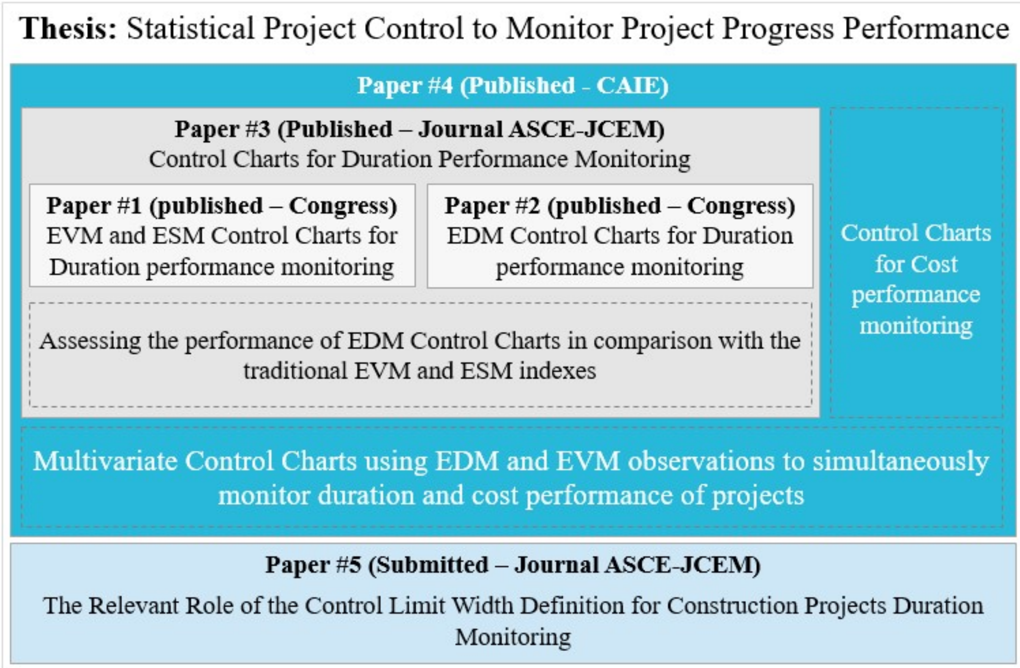
This is a paper-based thesis and it is organized into two parts. Part I of this work follows a traditional structure and focuses in the overall research objectives, contributions and how each paper supports them. This Chapter 1 contextualizes the research problem, its objectives and the thesis structure. Chapter 2 presents the notations used in this work and a brief introduction to the EVM, ESM, and EDM indexes, as well as to the control charts performance metrics. Chapter 3 presents the progressive process of the research and its phases. It also depicts each publication objectives and their main contributions. Chapter 4 summarizes the main findings of each paper and the manner how they integrate to each other towards accomplishing the overall thesis' objectives. Finally, Chapter 5 provides the research conclusions, limitations, and recommendations for future studies.

It is important to note that, in order to develop a comprehensive discussion about each publication and the integration among them, this first part presents several elements of the original papers, such as tables, figures, arguments, and paragraphs. However, for an extended overview of each publication the reader is referred to Part II of this document that presents the thesis' papers themselves, which are the central part of the research.

This paper-based thesis is based on five publications (presented in Part II). Paper #1 was presented in 2017 at the XLIX "*Simpósio Brasileiro de Pesquisa Operacional*" (SBPO) and is entitled "Statistical Project Control: Control Charts for Project Duration Monitoring" (Votto et al., 2017). Paper #2, Statistical Project Control with Earned Duration Management: Control Charts for Project Duration Monitoring (Votto et al., 2018) was presented in 2018 at the "XXXVIII *Encontro Nacional de Engenharia de Produção*" (ENEGEP). Paper #3 was published in 2020 at "Journal of Construction Engineering and Management" (JCEM) of the American Society of Civil Engineers (ASCE). It is entitled "Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring" (Votto et al., 2020a). Paper #4 was published in 2020 at "Computers & Industrial Engineering" (CAIE) with the title "Multivariate Control Charts Using Earned Value and Earned Duration Management Observations to Monitor Project Performance" (Votto et al., 2020b). Paper #5, "Earned Duration Management Control Charts: The Relevant Role of the Control Limit Width Definition for Construction Projects Duration Monitoring" is in the review process.

The details of each paper are appended at the end of this document. They can be access in the original Journal or Congress pages (the links are highlighted in the respective Appendix). Fig. 2 depicts the thesis structure and the overall relation among the publications.

Fig. 2: Paper-Based Thesis Structure



Source: Figure developed by the author for this thesis

2 NOTATIONS AND MONITORED VARIABLES

This chapter presents the notations and a brief introduction to the project control methodologies and to the metrics used to assess the control chart performance used in this work.

2.1 Project Control Notation and definitions

This section presents a brief introduction to the EVM, ESM, and EDM indexes, which are the monitored variables of this study. For extended overviews of the EVM, ESM, and EDM methodologies, the reader is referred to Anbari (2003), Lipke (2003), and Khamooshi and Golafshani (2014), respectively.

The aim of a project control and monitoring system is to detect the deviations from the project plan. It identifies and reports the project status, compares it with the plan, analyzes deviations, and implements appropriate corrective actions (Hazir, 2015). EVM is a well-known project control methodology that has attracted significant attention in the academic literature (Anbari, 2003; Fleming & Koppelman, 2005; Vandevoorde & Vanhoucke, 2006; PMI, 2013). It integrates the scope, the cost, and the schedule control into the same framework and provides performance indexes that allow managers to detect the cost overruns and the delays (Pajares & López-Paredes, 2011; Acebes et al., 2014; 2015).

Briefly, EVM is based on the parameters and variables measured at the project level (Fig. 3 shows a graphical representation of the EVM methodology). Let μPV_{it}, EV_{it}, and AC_{it} be the planned value, the earned value, and the actual cost of activity *i* at *t*, respectively. Once tracking each activity's progress along the project execution is not practical, EVM and its extensions aggregate the performance of individual activities and track them at the project level to provide the project team with an indication of the project progress status (Colin et al., 2015). Their sums related to all *n* activities are respectively denoted as the project's total planned value ($\mu\text{PV}_t = \sum_{i=1}^{n} \mu\text{PV}_{it}$), the total earned value ($\text{EV}_t = \sum_{i=1}^{n} \text{EV}_{it}$), and total actual cost ($\text{AC}_t = \sum_{i=1}^{n} \text{AC}_{it}$). Therefore, the parameter μPV_t is the cumulative planned cost for the planned work from the beginning of the project up to the review period *t* according to the baseline schedule. During the project execution, the variables AC_t and EV_t are periodically measured. They represent the actual cost incurred to accomplish the work performed and the cumulated planned cost to accomplish the total work performed from the beginning of the project up to the review period

t, respectively. These metrics are used to define the cost performance index (CPI_t) and the schedule performance index (SPI_t) at every period, as follow in the expressions (1) and (2)

$$\mathrm{CPI}_t = \frac{\sum_{i=1}^{n} \mathrm{EV}_{it}}{\sum_{i=1}^{n} \mathrm{AC}_{it}} = \frac{\mathrm{EV}_t}{\mathrm{AC}_t} \tag{1}$$

$$\mathrm{SPI}_t = \frac{\sum_{i=1}^{n} \mathrm{EV}_{it}}{\sum_{i=1}^{n} \mu\mathrm{PV}_{it}} = \frac{\mathrm{EV}_t}{\mu\mathrm{PV}_t} \tag{2}$$

These performance indexes can be thought of as efficiency ratios, in which the value one indicates that the performance is efficient and on target. More than one indicates an excellent performance and less than one indicates a poor project performance with cost or duration overrun, respectively (Anbari, 2003). For instance, SPI_t measures the overall work performed in terms of the earned value, in comparison with the work planned up to that point in time. At any time increment *t*, the project might have achieved more, less, or the same amount of work in comparison with the work planned to be achieved until that moment. Thus, this measure can have values greater, lower, or equal to one, respectively (Khamooshi & Golafshani, 2014).

Although the cost dimension of EVM is considered to be very effective, its schedule aspect has been questioned conceptually in the last few years. Many researchers have argued that SPI_t is not an accurate or reliable measure of the schedule performance because the monetary value of EV_t equals $\mu\mathrm{PV}_t$ in the end of the project and, therefore, SPI_t converges to one regardless of the actual duration (Lipke, 2003; Vandevoorde & Vanhoucke, 2006; Lipke et al., 2009; Khamooshi & Golafshani, 2014; Vanhoucke et al., 2015). To overcome this limitation, Lipke (2003) proposed ESM concept, in which the new earned schedule variable (ES_t) was introduced. It provides the actual schedule status of a project by estimating the duration at which the current EV was supposed to be earned (Lipke, 2003; Lipke et al., 2009; Hammad et al., 2018; Khamooshi & Abdi, 2016). This variable can be expressed in (3) as

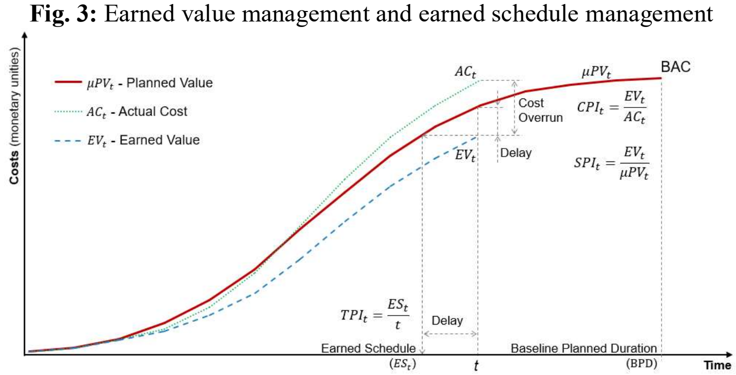
$$\mathrm{ES}_t = t_0 + \left(\frac{(\mathrm{EV}_t - \mu\mathrm{PV}_{t_0})}{(\mu\mathrm{PV}_{t_{0+1}} - \mu\mathrm{PV}_{t_0})}\right); \ \mu\mathrm{PV}_{t_0} \leq \mathrm{EV}_t < \mu\mathrm{PV}_{t_{0+1}} \tag{3}$$

The magnitude of ES_t is determined by projecting the cumulative EV_t curve onto the $\mu\mathrm{PV}_t$ curve (Fig. 3). Afterwards, it is divided by the actual date *t* to calculate the schedule performance index based on Earned Schedule. In this study, it is called Time Performance Index (TPI_t), (instead of the original notation $\mathrm{SPI(t)}_\mathrm{t}$, to avoid confusion with SPI_t from EVM). It is expressed in (4) as follows:

$$\mathrm{TPI}_t = \frac{\mathrm{ES}_t}{t} \tag{4}$$

By using ESM, some deficiencies of EVM can be overcome by monitoring the schedule indicator TPI_t throughout the entire project (Lipke, 2003; Hammad et al., 2018). Whereas many researchers agreed that the ESM method led to some improvements, recent studies argued that it also has conceptual shortcomings (Ghanbari et al., 2017a; Khamooshi & Abdi, 2016; Khamooshi & Golafshani, 2014; Votto et al., 2020). Although ES_t is measured in time units, it is based on the monetary values of EV_t and $\mu\mathrm{PV}_t$ (Eq. 3). Therefore, TPI_t still uses monetary terms to evaluate the schedule performance of a project (Khamooshi & Abdi, 2016). Furthermore, despite the possible correlations between the durations of activities and the cost items, the resulting duration and the cost profiles are not generally the same. The greater is their disparity, the poorer is the project duration performance. In such cases, both SPI_t and TPI_t produce inaccurate results, and sometimes, TPI_t can even perform worse than SPI_t, especially in the case of large long-term projects (Lipke et al., 2009; Khamooshi & Golafshani, 2014).

Fig. 3: Earned value management and earned schedule management



Source: Votto et al. (2020a)

To overcome those drawbacks, Khamooshi and Golafshani (2014) have recently developed the EDM concept that emphasizes the project duration control. In this method, the duration and the cost performance measures are completely decoupled, and the earned duration ED_t variable is introduced to measure the actual project duration (Khamooshi & Golafshani, 2014; Vanhoucke et al., 2015; Khamooshi & Abdi, 2016; Ghanbari et al., 2017a).

Therefore, let $\mu\mathrm{PD}_{it}$, AD_{it}, and ED_{it} be the planned, actual, and earned durations of activity i at time *t*, respectively. Their sums related to all activities are respectively denoted as the total planned duration ($\mu\mathrm{TPD}_t = \sum_{i=1}^{n} \mu\mathrm{PD}_{it}$), total actual duration ($\mathrm{TAD}_t = \sum_{i=1}^{n} \mathrm{AD}_{it}$), and total earned duration ($\mathrm{TED}_t = \sum_{i=1}^{n} \mathrm{ED}_{it}$). Note that $\mu\mathrm{TPD}_t$, TAD_t, and TED_t for EDM are the counterparts or equivalent twins of $\mu\mathrm{PV}_t$, AC_t, and EV_t for EVM (Khamooshi & Golafshani, 2014). Its graphical representation is shown in Fig. 4, where the cost is replaced by the duration (expressed in the units of time) on the vertical axis. Thus, these metrics are used to define the earned duration index (EDI_t) as follows:

$$\mathrm{EDI}_t = \frac{\sum_{i=1}^{n} \mathrm{ED}_{it}}{\sum_{i=1}^{n} \mathrm{\mu PD}_{it}} = \frac{\mathrm{TED}_t}{\mathrm{\mu TPD}_t} \tag{5}$$

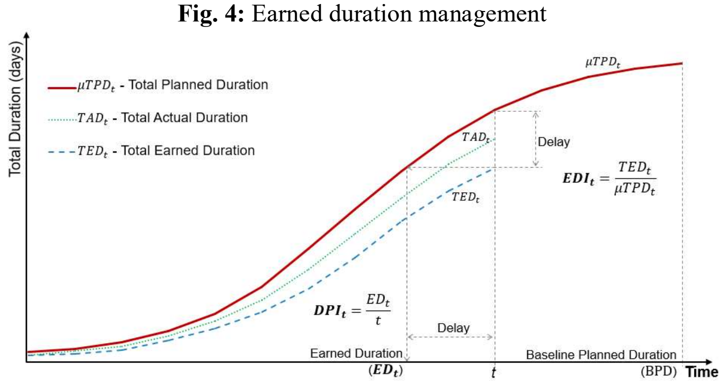
Similar to SPI_t, this indicator measures the overall work performed in terms of Total Earned Duration (TED_t) in comparison with the work planned ($\mathrm{\mu TPD}_t$) up to that point in time and can be greater, lower, or equal to one (Khamooshi & Golafshani, 2014). Furthermore, the earned duration (ED_t) variable measures the actual project progress in EDM (Khamooshi & Golafshani, 2014; Vanhoucke et al., 2015; Khamooshi & Abdi, 2016; Ghanbari et al., 2017a; 2017b). Its graphical representation is also depicted in Fig. 4. The earned duration on the actual date *t* is the date when the current TED_t should be achieved. ED_t can be expressed as

$$\mathrm{ED}_t = t_0 + \left(\frac{(\mathrm{TED}_t - \mathrm{\mu TPD}_{t_0})}{(\mathrm{\mu TPD}_{t_{0+1}} - \mathrm{\mu TPD}_{t_0})}\right); \ \mathrm{\mu TPD}_{t_0} \leq \mathrm{TED}_t \ < \mathrm{\mu TPD}_{t_{0+1}} \tag{6}$$

Thus, ED_t is divided by the actual date *t* to obtain the duration performance index (DPI_t), as follows:

$$\mathrm{DPI}_t = \frac{\mathrm{ED}_t}{t} \tag{7}$$

Fig. 4: Earned duration management



Source: Adapted from Khamooshi and Golafshani (2014) and Votto et al. (2020a)

Similar to TPI_t, DPI_t provides the measure of the progress performance on the critical path and toward completion of the project. Therefore, the value of DPI_t will be less than one, if the project is being behind the schedule. It will be equal to one, when the project is overall performing on schedule. Finally, it will be greater than one when the project is performing ahead of schedule. Thus, these EDM performance indicators can be monitored during the project execution to detect deviations from the baseline schedule.

Additionally, three additional notations are used. Let the $\mathrm{\mu BPD}_i$ and $\mathrm{\mu BPV_i}$ be the planned baseline duration and the planned baseline value of activity i. Their sums related to all activities at the end of the project are respectively denoted as the project's final total planned duration ($\mathrm{\mu TPD} = \sum_{i=1}^{n} \mathrm{\mu BPD}_i$) and the budget at completion ($\mathrm{\mu BAC} = \sum_{i=1}^{n} \mathrm{\mu BPV}_i$). Finally, the baseline planned duration ($\mathrm{\mu BPD}$) is the planned end date of the project considering the activities interdependences and relations described in the baseline schedule and by the project network.

2.2 Control Chart Performance Metrics

This section briefly presents the metrics used in this study to evaluate the performance of the proposed control charts. These metrics have been used in previous simulation project-control studies. For an extended overview, the reader is referred to Colin and Vanhoucke (2015b), Martens and Vanhoucke (2017), and Votto et al. (2020a).

The performance of a control chart is evaluated by the warning signals for each project execution and identifying whether the project is going to be completed on time or delayed. A warning signal is generated if the project performance index of a sample is not within the control limits of the respective control chart during any review period t. Such signals can be classified into two categories. A true positive is a correct warning signal that is generated when the project is past the deadline. In contrast, a false positive, which represents a type I error probability, is an incorrect warning signal made for the projects completed on time. In the same way, the lack of warning signals can be classified into two categories. True negatives are produced when no warning signals are created for a project that is completed on time. False negatives, also called type II error probabilities, correspond to a situation when no warning signals are generated for the late project executions (Martens & Vanhoucke, 2017). The first two performance measures of project control have been presented by Colin and Vanhoucke (2014) and were used in several studies (Colin & Vanhoucke, 2015a; 2015b; Martens & Vanhoucke, 2017; Votto et al., 2020a; 2020b).

The **detection performance** (DP) is defined as the probability that a warning signal is generated for late projects. It is also called the true positive rate because it measures the proportion of positives (i.e. late projects) that are identified as positives (i.e. generated warning signals) and represents the conditional probability of receiving a warning signal when the project is past the deadline (P [Signal | $Overrun$ Projects]). The detection performance should be as high as possible and it is the ratio of the sum of the late fictitious project executions that produced a warning signal during the review period t to the number of late executions (Colin & Vanhoucke, 2014; Martens & Vanhoucke, 2017) expressed in (8):

$$\textbf{Detection Performance} = \text{P [Signal} \mid \mathit{Overrun} \text{ Projects]} = \frac{\text{\# True Positives}}{\text{\# } \mathit{Overrun} \text{ Projects}} \tag{8}$$

The **probability of overreaction** (PO) is defined as the probability of receiving a warning signal for projects that do not exceed the expected budget and deadline. It is also called the false positive rate because it measures the proportion of negatives (i.e. projects within the expected budget and duration) that are identified as positives (i.e. generated warning signals). It represents the conditional probability of receiving a warning signal when the project is on schedule and budget (P [Signal | $as\ Planned$ Projects]). The probability of overreaction should be as low as possible (Colin & Vanhoucke, 2014; Martens & Vanhoucke, 2017). It is the ratio between the sum of the as planned fictitious project executions that generated a warning signal during the review period t (false positives) and the number of as planned executions in the set of simulation runs expressed in (9):

$$\mathbf{Probability\ of\ overreaction} = \text{P [Signal} \mid as\ Planned \text{ Projects]} = \frac{\text{\# False Positives}}{\#\ as\ Planned \text{ Projects}} \tag{9}$$

The detection performance and the probability of overreaction assess the control limits and identify whether warning signals are generated for different project outcomes. Nevertheless, in the real life, the outcome of a project is not known during its execution. Therefore, two other performance measures are used to accurately assess the performance of control charts: one defined by Colin and Vanhoucke (2015b) and a recent measure proposed by Martens and Vanhoucke (2017).

Efficiency is the probability that the project deadline or budget is exceeded when a warning signal is generated. Originally defined by Colin and Vanhoucke (2015b), this metric is also called as positive predictive value and represents the conditional probability of overrun in the presence of a warning signal during the review period t (P [$Overrun\ Project$ | Signal]). **Efficiency** can be expressed in (10) as

$$\mathbf{Efficiency} = P\ [Overrun \text{ Project} \mid \text{Signal}] = \frac{DP_t \times P[Overrun \text{ Projects}]}{\text{P[Signal]}_\text{t}} \tag{10}$$

and its value should be as high as possible. Finally, **reliability** is the probability that the project deadline or budget is exceeded when a warning signal is not generated. It is also called as negative predictive value and has been recently proposed by Martens and Vanhoucke (2017). Reliability should be as high as possible and represents the conditional probability that the project is going to be completed on time in the absence of a warning signal during the review period t (P [$As\ planned\ project$ |$no\ Signal$]). It can be expressed in (11) as

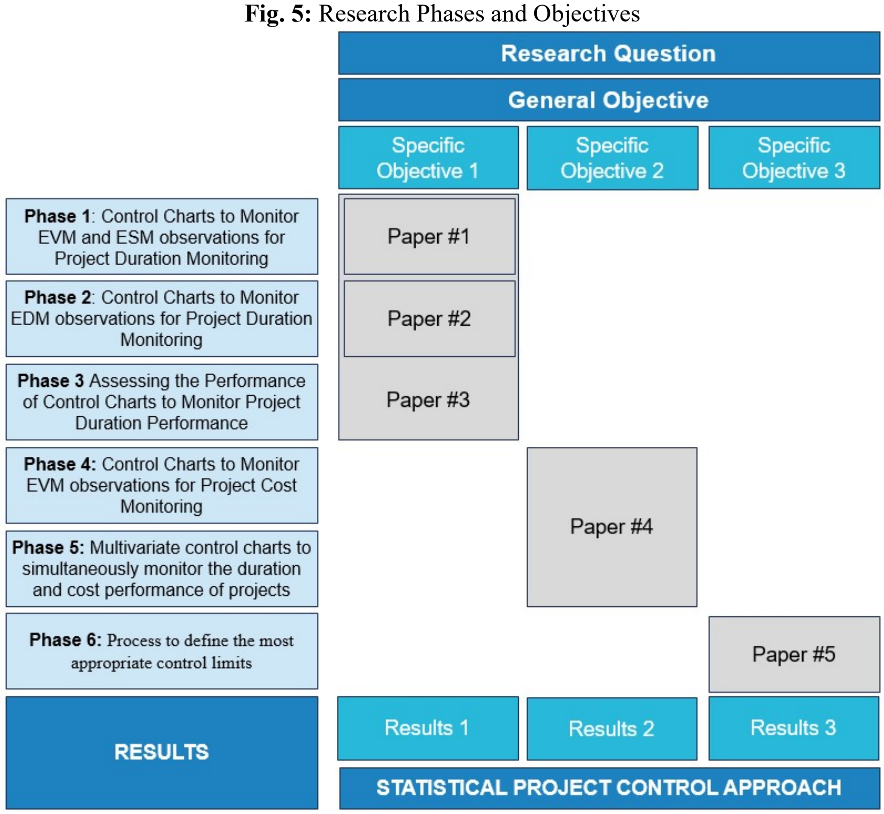
$$\mathbf{Reliability} = P[As\ planned \text{ Project} \mid \text{no Signal}] = \frac{(1 - PO_t) \times P[On\ time \text{ Projects}]}{P[\text{no Signal}]_t} \tag{11}$$

3 RESEARCH APPROACH

In order to achieve its objectives, this research has followed a progressive process to build the statistical project control approach to monitor the project progress. In this context, the three journal papers, that are the core of this study, cover each of the research specific objective in a comprehensive manner. Meanwhile, the two congress papers provide the bases of the literature review and support the first objective. It is worth noting that the output of some papers already indicated the rationale of a future research phase. Fig. 5 summarizes the research phases and how each paper is related to such phases and the research objectives.

The research approach adopted by this work, as well as by its papers, starts with a literature review to investigate the evolution and trends on the application of statistical process control for a project monitoring. Thus, the statistical project control methods were proposed in each research phase to address the identified literature gaps and single or multi-case studies are used to illustrate the application of the proposed methods on real-life projects. Later, especially in papers #3, #4, and #5, a quantitative research approach using simulation experiments is used to assess the performance of the proposed approach.

Fig. 5: Research Phases and Objectives



Source: Figure developed by the author for this thesis

3.1 Phase One: Literature Review and Control Charts to Monitor EVM and ESM Observations for Project Duration Monitoring

The starting point of the research was the investigation of the existing literature and the gaps on the use of statistical process control (SPC) charts to monitor the project performance on the earned value management (EVM) and earned schedule management (ESM) methodologies.

The implementation of SPC for project control aims to set the control limits to monitor the progress during the project execution based on a state of the statistical control reference. Vanhoucke (2019) classified the control limits project monitoring into three categories, the static, the analytical and the statistical control limits. The first category is restricted to randomly chosen values of the performance metrics that should not be exceeded. Rather than just setting thresholds using arbitrary values, the second category uses analytical control limits based on straightforward analytical calculations to better set the thresholds for project control, as the concept of the allowable buffer consumption.

In the third category, the control charts use statistical control limits (Vanhoucke, 2019). They can be built in different ways depending on how the state of control reference is determined. First, the control limits can be calculated based on historical data. During the project execution, periodic observations are plotted on the control charts. If these observations fall within the defined limits, the project is assumed to be in-control state. Otherwise, an abnormal periodic measurement out of the control limits indicates a schedule delay that is out of statistical control.

Although the previous researches on the use of control charts to monitor earned values indicators highlighted that it improves project control by providing an objectively based and easily implemented real-time monitoring system, the use of control limits based on historical data has been identified as a weakness of such an approach. It assumes the need to rely on historical data collected during the early phases of the project progress, or on data from similar projects from the past (Vanhoucke, 2019). The challenge for these methods lies in how the similarity among projects is defined once projects are unique endeavors. Indeed, some authors argue that the concept of similarity among projects is often vague and questionable, given the uniqueness nature of the projects (Colin & Vanhoucke, 2014).

The need to overcome the shortcoming of relying on historical data to determine the control limits is the rationale for the first phase of this research, which aims to answer the following question: *how to define the state of control reference based on simulated samples for project duration monitoring?* Until that point, the previous works on the use of control charts for project monitoring have concentrated on the use historical data to build a sample to determine stationary control limits for the whole project life cycle. The first work to propose the use of a simulated sample to determine the control limits was the seminal paper of Colin and Vanhoucke (2014). They used uniform probability function to describe the uncertainty in the duration of activities and performed Monte Carlo simulations to obtain samples of project executions. The outputs of the simulation are samples of the performance indicators. They are used to determine the control limits and to build the control charts to monitor earned value observations.

In this context, Paper #1 was produced to present the first steps of a statistical project control approach, with the control limits based on simulated samples to monitor the project duration progress. In this method, a simulation experiment is conducted to define a desired state of control. The acceptable deviation of each activity is defined using probability distribution functions (PDFs) assigned to describe the uncertainty in each activity duration. Thus, many durations X_i are simulated to provide an empirical in-control distribution of each indicator at every time t. The aim is to define the control limits such that they satisfy the desired performance level. For this reason, they are referred as probability control limits and are determined by simulated samples of each performance index in every review period t and represent a desired state of control (Votto et al., 2020b). Positive and negative deviations within a specified range are assumed to be inherent to any project and are considered to be normal. In contrary, some structural or systemic changes during the project life cycle can alter the initial expected variability and move the project performance outside of the control limits. Abnormal deviations exceeding a defined threshold should trigger further investigations and actions (Votto et al., 2020a).

Paper #1 and Paper #3 presented the control charts with probability control limits to monitor the schedule performance index (SPI_t) and the time performance index (TPI_t). It is worth noting that in this approach the probability control limits are non-stationary, that is, for each individual time increment t, new samples are simulated, and the control limit is determined. These control charts contribute to improve the capacity of EVM and ESM to interpret the deviations during the project execution phase by distinguishing between the expected deviations, when project is in statistical control, and the unexpected deviations, which can be interpreted as evidence of a real risk of the project delays.

In this sense, this first paper provided the first steps to build a more comprehensive approach for a project duration monitoring (presented in the following sections). Furthermore, Paper #1 applied these control charts to monitor the duration of a capital goods projects and triangular probability distribution functions (see Appendix F) were assigned to describe the uncertainty in each activity duration. Until that point, it could not be found any study on the literature with practical applications of such control charts with probability control limits

The major recommendation for future research of this phase was to measure the performance of the control charts and to use the proposed control charts to monitor the cost performance of projects. These research avenues built the motivation to the third and fourth phase of this thesis, presented in Sections 3.3 and 3.4, respectively.

3.2 Phase Two: Control Charts to Monitor EDM Observations for Project Duration Monitoring

Despite the contributions of the first study to the improvement of project duration monitoring, it mainly utilized EVM and ESM performance indexes, which used only cost-based data as proxies for assessing the projects duration performance. Although the durations and cost of activities may be mutually dependent, the project duration and cost profiles are not generally the same. The greater is their disparity, the poorer are the EVM and ESM duration performance measures (Khamooshi & Golafshani, 2014; Votto et al., 2020a). Therefore, the need for having a statistical control chart that uses only time-based data to monitor project duration provides the rationale for the second and third phases of this research.

Earned Duration Management (EDM) is the most recent extension of the earned value methodologies. It was originally proposed by Khamooshi and Golafshani (2014) to emphasize the time dimension of projects and to address the shortcomings of EVM and ESM caused by the usage of cost-based metrics as proxies for assessing the project duration performance (Vanhoucke et al., 2015). While EVM and ESM measure project progress based on the comparison between the monetary values of planned value (µPV), actual costs (AC) and earned value (EV), EDM completely decouples the cost dimension to measure the duration performance of projects using exclusively time-based data for the generation of progress indicators (Vanhoucke et al., 2015; Ghanbari et al., 2017a). In this methodology, the planned, actual and earned values s-curves are replaced by the total planned duration (μTPD), total actual duration (TAD), and the total earned duration (TED), respectively.

After the seminal work of Khamooshi and Golafshani (2014), several studies have recognized EDM's benefits over other earned value methodologies due to its independence from the monetary values (Batselier & Vanhoucke, 2015; Khamooshi & Abdi, 2016; Borges & Mario, 2017; Ghanbari et al., 2017a; 2017b; Vanhoucke, 2017; de Andrade et al., 2019). For instance, Batselier and Vanhoucke (2015) compared the performance of different deterministic state-of-the-art forecasting approaches for project duration based on EVM, ESM, and EDM. They concluded that EDM was a valid methodology and that DPI_t could be potentially utilized to improve the EVM and ESM methods (Batselier & Vanhoucke, 2015). Khamooshi and Abdi (2016) used EDM in conjunction with an exponential smoothing forecasting technique to predict the completion of a project. Their findings indicated that the EDM performance indexes were a preferred option compared with ESM. Ghanbari et al. (2017a; 2017b) proposed fuzzy approaches to measure the project performance based on the EDM methodology.

Nevertheless, the use of EDM performance indicators remained restrict to deterministic project control approaches for a long time. Until the beginning of phase two, to the best of the author's knowledge, no study on the use control charts to monitor project duration had been found in the literature. To cover this gap, the aim of phase two was to propose the use of control charts to monitor the duration performance of projects using exclusively time-based indexes from EDM, instead of the more traditional schedule performance indexes, presented before. Similar to the previous phase, it uses probability control limits, determined by simulated samples, to interpret deviations during the project execution by distinguishing between the common and the special sources of variation.

Paper #2 and Paper #3 presented the use of such control charts to monitor the duration performance index (DPI_t) from EDM in a real engineering, procurement and construction (EPC) project. In this context, the main contribution of Paper #2 lies in the introduction of control charts with probability control limits to monitor the recent proposed DPI_t in a real project. The results suggest DPI_t as a promising alternative for a project duration performance monitoring and highlight that this probabilistic approach can improve the ability of EDM in detecting duration deviation during a project execution.

The major recommendation of future research of this phase is the performance comparison of EDM's control charts with the more traditional schedule performance indicators from EVM and ESM methodologies. This research avenue provides the rationale for the third phase of this thesis.

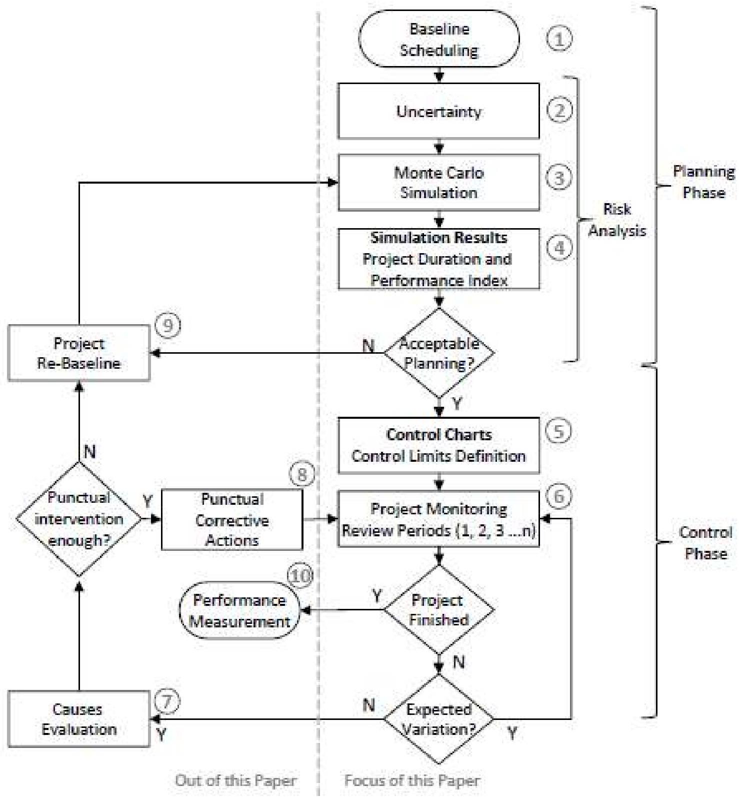
3.3 Phase Three: Statistical Project Control Approach and EDM Control Charts Performance Assessment

As an extension of previous research phases, phase three aims to propose a comprehensive Statistical Project Control Approach to monitor the duration performance of projects and to assess the performance of different control charts. It aims to answer the following question: *Can the use of a time-based index improve the ability of project duration control charts to distinguish between acceptable and not acceptable variations and trigger appropriate actions when the observed variation in project's progress exceeds a certain predefined threshold?*

In this context, the first main contribution of paper #3 was to propose a comprehensive statistical project control approach to monitor the duration project performance using indicators only time based. The approach is grounded on the risk analysis (Hulett, 1996; Hulett, 2009; Vanhoucke, 2011), the dynamic scheduling (Vanhoucke, 2012), and the control charts (Woodall & Montgomery, 1999; Montgomery, 2009). Fig. 6 shows the flowchart that summarizes the proposed approach.

The proposal requires a project-planning phase that consists of a baseline schedule and a project risk analysis. It includes the project network with its activities, dependencies, and durations, which serves as a reference point for the subsequent steps (step 1). The uncertainty is modeled by probability distribution functions to produce estimates of the durations of activities (step 2) and the overall risk of the entire project schedule can be evaluated by performing extensive Monte Carlo simulations (step 3). The total duration and periodic performance indicators are recorded in each simulation run. Thus, the empirical probability distribution function of the project duration is used to estimate the probability that a project will be completed by a specific date or to predict the most likely end date. The estimated forecasts can be compared with the project targets by considering several aspects, including the contract definition, the customer expectations, the management decisions, and the monetary or the time constraints (step 4). In this step, the output of the simulation also provides the samples of the performance indicators and their empirical cumulative probability functions (CDF) to determine the probability control limits.

Fig. 6: Statistical Project Control Approach for Duration Performance Monitoring



Source: Votto et al. (2020a)

If the current plan is not acceptable with respect to the project targets and the risk analysis, it must be rescheduled (step 9) under different assumptions, and the previous steps repeated. If the current plan is acceptable, the next step (step 5) is to build the control charts. Thus, it is used to monitor the execution of the actual project by plotting the periodic performance indicators (step 6). The observations that fall within the control region indicate that the project is statistically in-control and that only common causes or expected variations are present.

In contrast, the observations that fall below the lower control limit (LCL) represent warning signals that indicate an abnormal project behavior caused by the special variation sources that can influence the expected result. In these situations, the project team has to thoroughly investigate the cause of variation to determine how to bring the project back on track (step 7). In many cases, small and punctual corrective actions are sufficient to return the project back to the baseline schedule (step 8); however, the project team sometimes is forced to reschedule the entire project (step 9). Meanwhile, the control charts can also be used to explore opportunities in cases when the project proceeds better than the expected, which are represented by observations higher than the upper control limit (UCL) of the monitored variable. In these cases, the project team can also decide to reschedule the project (step 9).

The application of the described method to a real-life situation was presented and demonstrated that the ability of distinguishing between acceptable and not acceptable variations could be improved by using the proposed statistical control charts with probability control limits obtained by simulations instead of intuitive fixed thresholds based on the practical experience.

Paper #3 consolidated the results of Paper #1 and #2 and its second contribution lies in the assessment of EDM control charts performance in comparison with the traditional EVM and ESM indexes. First, an ex post facto comparison with the real project data was performed. Furthermore, an extensive simulation experiment was conducted to assess the performance of the proposed control chart in different scenarios. In order to determine the discriminative power of the proposed control charts, additional out-of-control project executions, in which each activity duration may exhibit unacceptable variations, were simulated. The analysis was conducted in different project periods to evaluate the performance of each indicator during a project lifecycle.

The results of the computational experiments (summarized on Section 4.1) demonstrated generally good performance of the proposed control charts and highlight DPI_t as a promising alternative for project duration performance monitoring. It demonstrates that the use of DPI_t can improve the ability of the developed statistical control charts to distinguish between acceptable and not acceptable variations and trigger appropriate actions when the variation of project's progress exceeds certain predefined statistical thresholds.

The paper pointed out that its results should be interpreted with care. The strict focus on the duration performance of projects and lack of integration between the duration and cost performance was a potential weakness in terms of the quality of the feedback provided to the project team. The utilization of this method using multivariate control charts to simultaneously monitor the project cost and duration based on the control limits produced by simulations was recommend as an opportunity of a future research in this area, which was explored in the fifth phase of this research (Section 3.5)

3.4 Phase Four: Control Charts to Monitor EVM Observations for Project Cost Monitoring

Despite the contributions of the previous studies to the improvement of project monitoring, they concentrated exclusively on the time dimension of the project performance and assumed that the cost variation of each activity is a linear function of its duration. They argument that this lack of focus on the cost performance monitoring of projects was a potential weakness of the proposed method. Consequently, emerging from the perception that there was still a gap on the literature about the use of control charts with probability control limits to monitor the cost performance of projects, the aim of the fourth phase was to incorporate the cost monitoring into the statistical project control approach.

In this context, to the best of the author's knowledge, Paper #4 was the first paper in the literature to present the use of control charts with probability control limits determine by simulated samples to monitor the Cost Performance Index (CPI_t), from Earned Value Management methodology, in a real project. As a first contribution of Paper #4, it proposed to enhance step 3 and 4 of the previous method (Fig. 6). Thus, Monte Carlos simulation is also used to provide the sample and the in-control empirical distribution function of CPI_t at every review period *t*. This output is used to determine the probability control limits of CPI_t control chart.

The study presented three scenarios of cost variation to analyze the performance of the proposed control chart using different measures. The results showed that CPI control charts presented a very high detection performance in all scenarios and that its efficiency increases for projects with a higher probability of cost overrun.

3.5 Phase Five: Multivariate Control Charts to Simultaneously Monitor the Duration and the Cost Performance of Projects

As stated by paper #4, applying separated univariate control charts to each index is a possible solution; however, it may be inefficient and lead to erroneous conclusions, primarily when the components of the monitored vector are mutually correlated (Montgomery, 2009). There is a principle that states that what emerged together should be analyzed together (Mestek et al., 1994). A possibility is to consider the monitoring of two or more indicators simultaneously by a multivariate control chart which considers their relationship. A common method of constructing multivariate control charts is based on Hotelling's T^2 statistic, which is the analogue of the Shewhart chart (MacGregor & Kourty, 1995; Montgomery, 2009).

In this context, the fifth phase of this research investigated the use of multivariate control charts to simultaneously monitor the duration and cost performance of projects. The rationale for this phase is twofold. First, the reliance on univariate control charts might lead to unsatisfactory results such as an increase in the rate of false alarms, particularly when the variables are correlated. Several studies indicated that the practice of monitoring the stability of the process with more than one correlated quality characteristic using univariate control charts increases the probability of false alarms of special causes of variation (El-Din et al., 2006; Montgomery, 2009; Ryan, 2011; Santos-Fernández, 2012; Hadian & Rahimifard, 2019).

Second, the project duration and the cost analysis have always to be performed simultaneously once they can be correlated and the action to keep one under control can have large consequences on the other. For instance, some decisions to minimize the cost overruns of some activities can increase the duration of one or more activities (e.g. purchasing cheaper material with longer lead-time). Moreover, the project team can be compelled to spend more effort or money to compensate delays in some activities (e.g. changing a transport from sea freight to air freight or using overtime and additional manpower to minimize a delay in some activities).

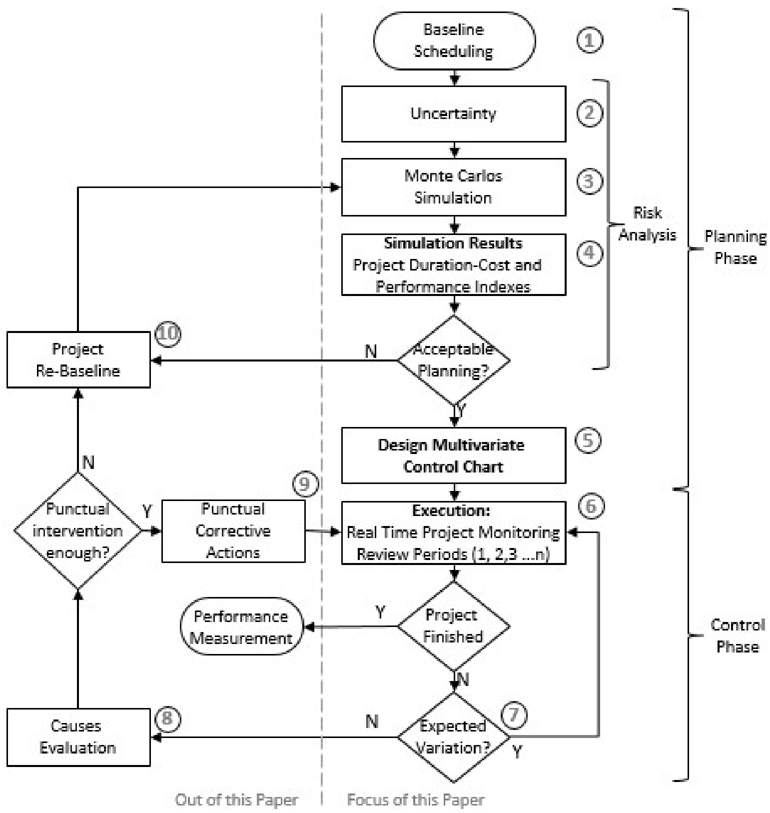
Only two studies had proposed multivariate methods to monitor project progress in the literature. First, Colin et al. (2015) used multivariate control charts to monitor EVM and ESM indicators in a schedule control approach without considering the cost dimension. Later, Hadian and Rahimifard (2019) proposed a multivariate control chart to monitor project performance using only EVM indexes. Their control chart uses historical data to calculate a static control limit for the entire project.

Despite the contributions of that study to the improvement of project control, it uses the schedule performance index (SPI_t) from EVM to monitor the project duration performance. SPI_t has been largely argued as not being the most accurate duration measure because it uses cost-based data as proxies to assess project duration performances (Lipke, 2003; Vandevoorde & Vanhoucke, 2006; Lipke et al., 2009; Khamooshi & Golafshani, 2014). The use of control limits based on historical or progress data was also identified as a weakness of such an approach (Vanhoucke, 2019).

To the best of the author's knowledge, the DPI_t, from EDM, had not been used in a multivariate statistical project control approach, and no study had been conducted on the use of multivariate control charts with probability control limits to simultaneously monitor the duration and the cost of projects.

In this context, the main objective and contribution of paper #4 was to propose a statistical project control approach using multivariate T^2 control charts to simultaneously monitor the duration and cost performance of projects (Fig. 7). It can be noted that it is an extension of the method proposed by Paper #3 and uses the CPI_t, from EVM, and the DPI_t, from EDM, to build a new multivariate project control statistic.

Fig. 7: Multivariate statistical project control approach to monitor project performance



Source: Votto et al. (2020b)

Similar as the previous phases, the duration and cost of activities are described by probability distribution functions (PDFs) and the output of Monte Carlo simulation provides the samples of each periodic indexes, which build the vector $\mathbf{W}_{0t} = (\mathrm{DPI}_{0t}, \mathrm{CPI}_{0t})$. Thus, this output allows the calculation of the new periodic statistic T^2_{0t} at any t, as follows:

$$T^2_{0t} = (\mathbf{W}_{0t} - \boldsymbol{\mu}_{0\mathrm{W}_t})' \sum\nolimits_{0\mathrm{W}t}^{-1} (\mathbf{W}_{0t} - \boldsymbol{\mu}_{0\mathrm{W}_t}) \tag{12}$$

In practice, this means that a pre-defined state of control reference exists for each review period t represented by the mean vector $\boldsymbol{\mu}_{0\mathrm{W}_t}$ and the covariance matrix $\boldsymbol{\Sigma}_{Wt}$. Consequently, and for independence with respect to distributional assumptions, the in-control empirical distribution of T_{0t}^2 is used to determine the control limits for each review period t. Thus, the control limits L_t of the proposed T2-type chart are determined for each period t such that $P(T_t^2 > \mathrm{L}_t) = \alpha$, where α is the Type I error. When the project is in execution, at any t, the vector of observations $\mathbf{W}_t = (\mathrm{DPI}_t, \mathrm{CPI}_t)$, is available. Subsequently, the statistic T_t^2 can be obtained as the monitored statistic, using expression (13):

$$T_t^2 = (\mathbf{W}_t - \boldsymbol{\mu}_{0\mathrm{W}_t})' \sum\nolimits_{0\mathrm{W}t}^{-1} (\mathbf{W}_t - \boldsymbol{\mu}_{0\mathrm{W}_t}) \tag{13}$$

Thus, whenever $T_t^2 > \mathrm{L}_t$, the control chart will signal. It indicates the presence of special sources of variation, interpreted as evidence of real risk of project delays and cost overrun.

A second contribution of Paper #4 was the assessment of the proposed charts performance in comparison with different univariate control charts and other multivariate control charts. The results (summarized in Section 4.2) demonstrated that the proposed approach exhibited a good performance facilitating the interpretation of actual deviations during the project execution, distinguishing between the common and the special sources of variation. It was argued that, although the detection performance of the new approach can be lower than some univariate control charts (particularly, the DPI_t chart), the multivariate control charts using DPI_t and CPI_t can reduce the false alarms rate and exhibited much higher efficiency than all the tested alternatives.

3.6 Phase Six: Setting the Appropriate Control Limit Width

Previous studies have focused on the construction of different control charts and in their performance assessment. Nevertheless, a critical decision to build a statistical project control chart is the control limit width, defined by a Type I error (α), which has a strong influence on the control chart performance (Colin & Vanhoucke, 2014. Votto et al., 2020a).

There is a trade-off between the performance of the control chart and the control effort to investigate the cause of the warning signals (Colin & Vanhoucke, 2015b). Consequently, the most important feature of a control chart is the performance to identify the special sources of variation during the project execution that enables the project team to focus only on real deviations and avoid spending unnecessary effort to drill down to the activity level to search for false alarms.

Therefore, the central question of phase six is: *Which factors can influence the decision of the appropriate control limit width to monitor project duration using EDM performance indicators, and how to predefine the level α to determine the control limits depending on such factors?*

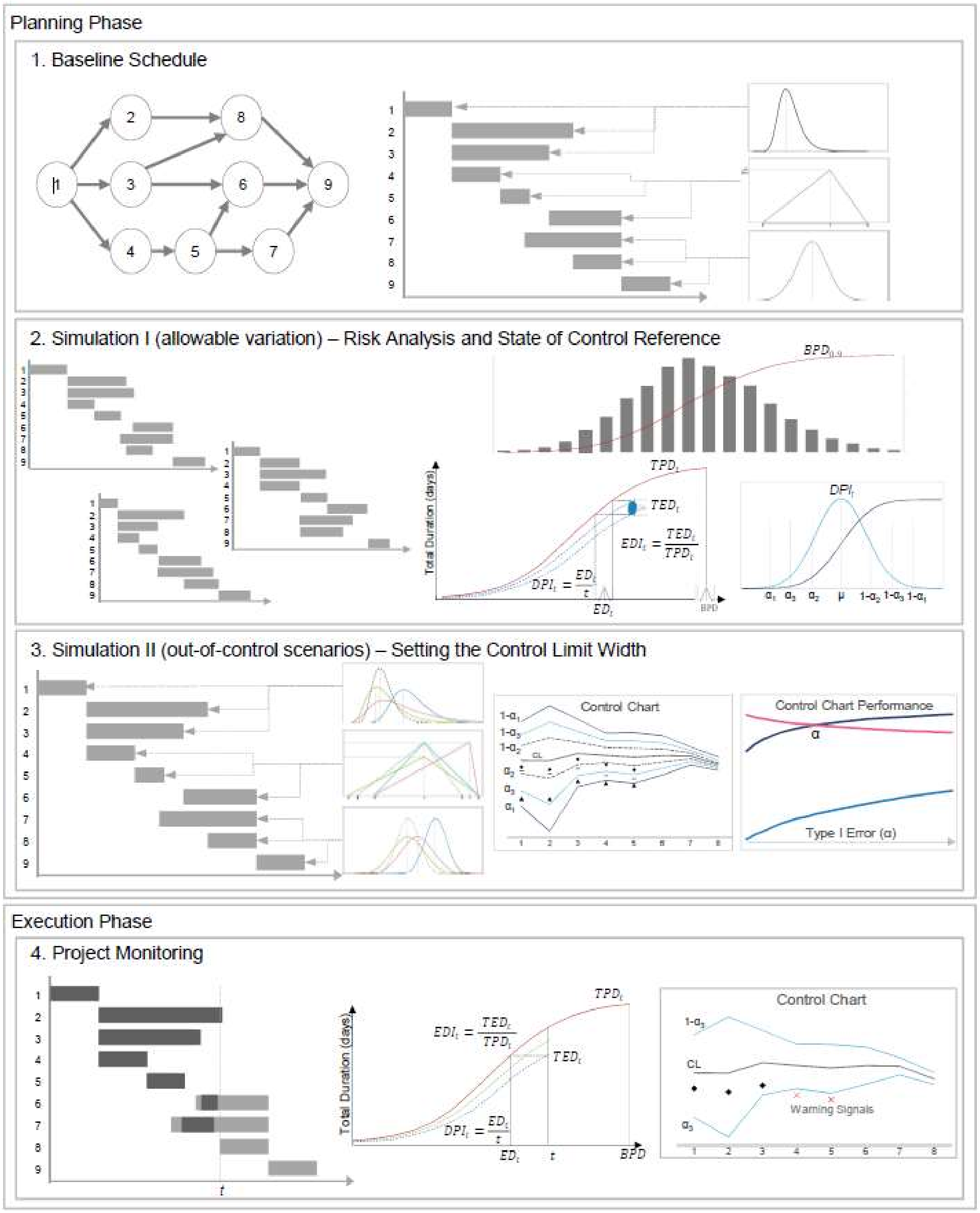
Previous studies only suggested directions to define the level α. Mortaji et al. (2018) recommended setting a low value of α to reduce the effort to find out the source of the variation. Colin and Vanhoucke (2014) showed that an appropriate choice for α should balance the risk of project delays and the willingness to invest effort in false alarms. However, these studies do not consider a decision-making process to select the appropriate control limit width. Instead, they present numerical examples in which the parameter α is arbitrarily chosen. Recently, Chen et al. (2020) proposed an algorithm to optimize the control limits. Despite the contribution of this study, it does not consider the different project targets and uncertainty scenarios that can influence this decision. To the best of the author's knowledge, there was no method in the literature to support the choice of the most appropriate width of the control limits, depending on its targets and risk management decisions.

In this context, as an extension of the method proposed in the previous phases, paper #5 has been produced with the objective to call attention to the relevant role that the appropriate definition of the control limit width plays in project control and in the performance of control charts to monitor the duration of construction projects. It incorporates a decision-making process, to define the most appropriate control limit width for a project, into the statistical project control approach using control charts with probability control limits. Fig. 8 depicts the proposed approach.

The first two steps followed the previous approaches. First, the definition of baseline schedule and the risk analysis, in which the variation of each activity is limited to an acceptable margin from the planned values. Later, the use of the simulation output is used to calculate the periodic indicators of each run and to obtain the empirical distribution of each indicator for every period, providing the required simulated sample to determine the control limits.

Thus, the third step introduces a new simulation experiment in the project planning phase to determine the discriminative power of the control charts. This time, additional out-of-control project executions, in which the activities duration may exhibit unacceptable variation, are simulated. Different out-of-control scenarios can be proposed for the random variation of the activity durations depending on the risk analysis conducted by the project team. The target of this new step is to measure the ability of the control chart to distinguish between acceptable and unacceptable variations under different control limit widths.

Fig. 8: Statistical project control approach to set the appropriate control limit width



Source: Paper #5

In this method, the control chart performance is measured according to the generation or not of warning signals for each project execution and identifying whether the simulation run is completed on time or delayed. Three performance measures are used to balance the different project targets: the detection performance, the probability of overreactions, and the efficiency.

These performance measures were used in previous simulation project control studies to evaluate the control charts performance (Martens & Vanhoucke, 2017; Votto et al., 2020a; 2020b). Nevertheless, to best of the author's knowledge, they have never been used to support setting the most appropriate width of the probability control limits in project planning phase.

Later, with the appropriated probability control limits defined, it is possible to build the control chart and monitor the actual project execution by plotting the periodic performance indicators and observing whether they are within the control limits or not, similar to the approach presented in the previous phases.

Therefore, this method works as a decision-making process to support the project team in the selection of the appropriate control limit width for a project, depending on its specific aspects. The results of the computational experiments (see Section 4.3) confirmed the trade-off between the performance of the control charts and the control effort to investigate the cause of every warning signal. It highlights that the preferable choice of α is strongly influenced by different project duration targets, risk and uncertainty scenarios estimated in the planning phase, and the team's risk profile.

4 RESEARCH RESULTS

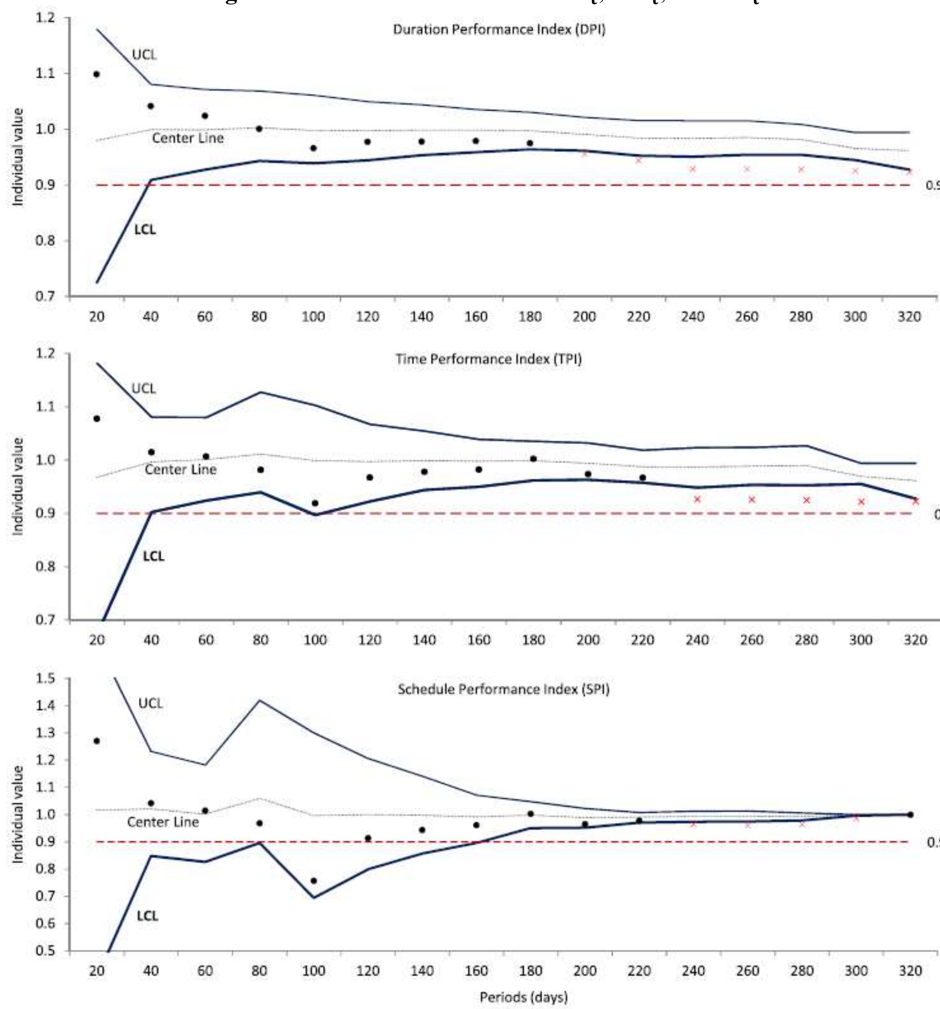
In this chapter the results are organized to cover each specific objective of the thesis. The aim is summarizing the main findings of each research paper and to consolidate the thesis' results. It is worth noting that the results emerge from the publications themselves and from the interaction among them, as they follow the progressive approach presented in Chapter 3. The objective of this chapter is not to describe each paper's result in detail. Instead, the aim is to briefly depict their main findings that cover each research specific objective, connecting the papers and each research phases, in order to build the overall PhD thesis and its contributions.

4.1 Specific Objective 1: Propose and assess the use of EDM's time-based index to improve the performance of control charts for project duration monitoring

As described in Section 1.2 the first specific objective is to analyze how the use of EDM's time-based index can improve the performance of the control charts to monitor the duration performance of projects. To accomplish this objective, the first three papers proposed the use of different control charts to monitor the project duration performance of a real-life EPC project project. The project network, the PDF parameters of the activity durations and costs, and the project baseline planned duration (μBPD) and budget at completion (μBAC), considering the deterministic planed values, are presented in Appendix G (numerical example A). For an extended view of all project details, the reader is referred to Paper #3. The procedure in Fig. 6 is followed. Fig. 9 shows the individual control charts for SPI_t and TPI_t (proposed in Paper #1 and #3), and DPI_t (proposed in the Paper #2 and #3).

Meanwhile, the Papers #1 and #2 recommend as future research the evaluation of the control charts performance. In particular, Paper #2, recommended to compare the performance of DPI_t control charts with the more traditional schedule performance indicators. In this context, and evolved from the previous two publications, one of Paper #3's major contribution was to present a performance comparison of the recently proposed DPI_t index, from EDM methodology, with the well-known SPI_t and TPI_t indexes, from EVM and ESM methodologies, respectively. The analysis was conducted in different periods to evaluate the performance of each indicator during a real project lifecycle. First, an ex post facto analysis with the real project data was conducted. The periodic observations of each index are plotted (• or ×) in the control charts of Fig. 9. It shows that the ability of distinguishing between acceptable and not acceptable variations can be improved when the proposed statistical control charts with the probability control limits obtained by simulations are utilized instead of intuitive fixed thresholds based on the practical experience. Furthermore, although the three control charts have detected the deviation from the baseline schedule, the DPI_t chart did it faster (over a review period of 200 days) than the other performance indexes (240 days).

Fig. 9: Individual Control Charts: $\mathbf{DPI_t}$, $\mathbf{TPI_t}$, and $\mathbf{SPI_t}$



Source: Votto et al. (2020a)

For a more comprehensive analysis, a second simulation experiment was conducted to measure the ability of the DPI_t control chart to evaluate the project duration performance and to compare it with those of the traditional SPI_t and TPI_t metrics. To determine the discriminative power of the proposed control charts, additional out-of-control project execution simulations, in which each activity duration may exhibit unacceptable variations, were performed. Five out-of-control scenarios were proposed for the random variation of the activity duration to simulate different uncertainty situations for the EPC project (Table 1).

Table 1: Simulation scenarios and duration output (Paper #3)

Scenarios		Distribution Parameters			Simulation output			
m	**Activities**	Min a_{jm}	ML c_{jm}	Max b_{jm}	μ Duration	90th quantile	Delays %	On Time %
Planned 0	**j={2, 3,...,35}**	a_{j0}	c_{j0}	b_{j0}	312	320	10	90
1	**j={2, 3,...35}**	a_{j0}	c_{j0}	$1.1b_{j0}$	329	341	83	17
2	**j={2, 3,…,35}**	a_{j0}	$1.1\ c_{j0}$	b_{j0}	322	330	60	40
3	**j={2, 3,…,8}**	a_{j0}	$a_{j0} + 0.8\ (b_{j0}- a_{j0})$	b_{j0}	316	324	24	76
4	**j={20, 21,...,27}**	a_{j0}	$a_{j0} + 0.8\ (b_{j0}- a_{j0})$	b_{j0}	316	324	22	78
5	**j={8, 13, 15, 16, 17, 33}**	a_{j0}	b_{j0}	b_{j0}	321	333	52	48

Source: Votto et al. (2020a)

The performance analysis is depicted in Table 2. A first finding indicated that SPI_t and TPI_t control charts exhibit the same performance in all five scenarios and projects phases. These result do not support the common assumption stating that during the last project stage, SPI_t becomes unreliable when the project completion is delayed (Lipke, 2003; Vandevoorde & Vanhoucke, 2006; Khamooshi & Golafshani, 2014). It is clear that if the project team uses a fixed value (such as a threshold of 0.9 or a static control limit) as the warning level for SPI_t, at the end of the project, it will lose the ability to identify schedule deviation since SPI_t converges to one. Nevertheless, if the proposed control charts with non-static probability control limits are used to monitor the duration performance, SPI_t becomes as reliable as TPI_t during the entire project lifecycle.

Table 2: Control charts performance analysis (Paper #3)

Scenarios		**Detection Performance**			**Probability of Overreaction**			**Efficiency**			**Reliability**		
		1st third	2nd third	**Final**	1st third	2nd third	**Final**	1st third	2nd third	**Final**	1st third	2nd third	**Final**
		$t \leq 100$	$t \leq 200$	$\boldsymbol{t \leq 300}$	$t \leq 100$	$t \leq 200$	$\boldsymbol{t \leq 300}$	$t \leq 100$	$t \leq 200$	$\boldsymbol{t \leq 300}$	$t \leq 100$	$t \leq 200$	$\boldsymbol{t \leq 300}$
1	SPI_t	0.47	0.77	0.91	0.14	0.32	0.47	0.94	0.92	0.90	0.25	0.38	0.54
	TPI_t	0.47	0.77	0.91	0.14	0.32	0.47	0.94	0.92	0.90	0.25	0.38	0.54
	DPI_t	0.48	0.76	**0.96***	0.14	0.26	**0.38***	0.94	0.93	**0.92***	0.26	0.39	**0.75***
2	SPI_t	0.41	0.75	0.86	0.13	0.39	0.52	0.83	0.74	0.71	0.50	0.63	0.71
	TPI_t	0.41	0.75	0.86	0.13	0.39	0.52	0.83	0.74	0.71	0.50	0.63	0.71
	DPI_t	0.46	0.75	**0.92***	0.14	0.35	**0.43***	0.83	0.76	**0.76***	0.52	0.64	**0.82***
3	SPI_t	0.67	0.78	0.85	0.32	0.43	0.47	0.40	0.37	0.37	0.87	0.89	0.92
	TPI_t	0.67	0.78	0.85	0.32	0.43	0.47	0.40	0.37	0.37	0.87	0.89	0.92
	DPI_t	0.66	0.73	**0.88***	0.31	0.36	**0.38***	0.40	0.39	**0.42***	0.86	0.88	**0.94***
4	SPI_t	0.30	0.46	0.81	0.09	0.15	0.30	0.48	0.47	0.44	0.82	0.85	0.93
	TPI_t	0.30	0.46	0.81	0.09	0.15	0.30	0.48	0.47	0.44	0.82	0.85	0.93
	DPI_t	0.25	0.48	**0.83***	0.08	0.14	**0.23***	0.47	0.49	**0.51***	0.81	0.85	**0.94***
5	SPI_t	0.47	0.59	0.65	0.10	0.15	0.19	0.83	0.81	0.78	0.61	0.66	0.68
	TPI_t	0.47	0.59	0.65	0.10	0.15	0.19	0.83	0.81	0.78	0.61	0.66	0.68
	DPI_t	0.32	0.43	**0.87***	0.08	0.12	**0.14***	0.81	0.80	**0.87***	0.56	0.59	**0.86***

Note: Values in bold (*) highlight the duration index with the best performance at the end of the project for each scenario.
Source: Votto et al. (2020a)

A second result from the assessment is the good overall detection performance and the probability of overreaction of the control charts used in the case study, which confirms the relevance of the proposed approach. Nevertheless, the performance in terms of efficiency varies in each scenario. The developed control charts demonstrated higher efficiency in the scenarios with higher probabilities of project delay. However, the control chart efficiency decreases dramatically when the probability of a project delay is very low due to the small change in the mean of the final duration. These results can be explained by the fact that the Shewhart control charts are known to detect large changes in the process mean or variance caused by the special sources of variation, however they are not efficient to detect smaller changes (Hawkins and Zamba, 2003; Montgomery, 2009). To overcome such problem, other control charts that detect smaller changes more efficiently can be developed as future research.

Finally, the outcome of the experimental study also indicated the general better performance of DPI_t as compared with that of the traditional SPI_t and TPI_t control charts observed in all proposed scenarios. Therefore, despite the limited scope of the study (caused by the single project simulation), it highlighted the proposed DPI_t chart with probability control limits as a promising alternative for the project duration control. These findings accomplish the first objective and demonstrated that the use of the time-based DPI_t, from EDM, can improve the ability of the developed statistical control charts to distinguish between acceptable and not acceptable variations and trigger appropriate actions when the variation of project's progress exceeds certain predefined statistical thresholds.

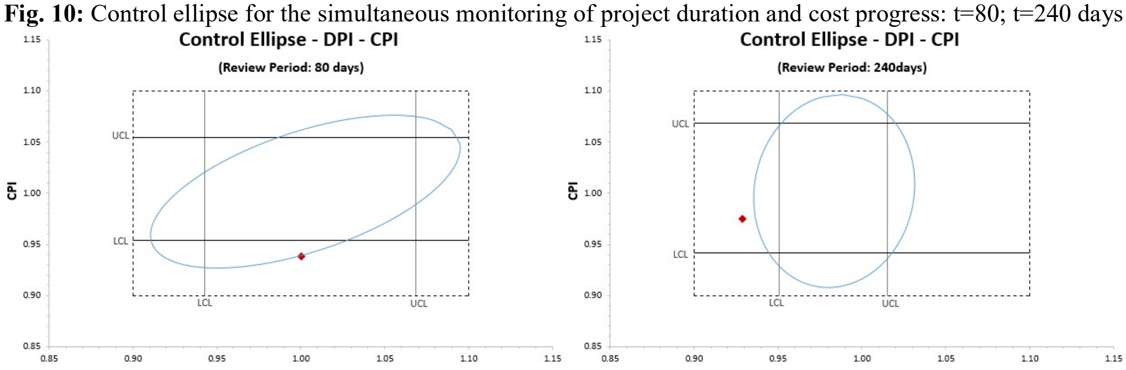
4.2 Specific Objective 2: Propose and Asses the Use of Multivariate T^2 Control Charts to Monitor the Duration and Cost Performance of Projects Simultaneously

As presented in previous chapters and sections, the lack of integration between the duration and the cost performance is a potential weakness in terms of the quality of the feedback provided to the project team. In this sense, the second specific objective of this thesis is to apply and assess the performance of multivariate T^2 control charts to simultaneously monitor the duration and the cost performance of projects. To accomplish this objective, the major contributions of Paper #4 are threefold. First, the use of a single chart to monitor both dimensions simplifies the project control system and decreases the false alarms rate. Second, simulated samples were used to determine the control limits for each review period based on the allowable cost and duration variation of each activity. Finally, the use of the multivariate approach to monitor the recently proposed DPI_t, which utilizes only time-based metrics, in contrast with more traditional methodologies that use cost-based data as proxies to assess the performance of a project's duration.

The application of the proposed method on a real-life EPC project is presented. The project network, the PDF parameters of the activity durations and costs, and the project baseline planned duration (μBPD) and budget at completion (μBAC), considering the deterministic planed values, are presented in Appendix G (numerical example A). For an extended view of all project details, the reader is referred to Paper #4. To illustrate the use of the method, the procedure in Fig. 7 is followed and Monte Carlo simulation experiments are performed. First, the variation was limited to an acceptable margin from the planned values. The values of the random variables (EV_t, AC_t, ED_t) in each simulation were recorded to calculate each periodic performance indicators. The output of the simulation was used to calculate the in-control vector $\boldsymbol{\mu}_{0\mathrm{W}_t} = (\overline{\mathrm{CPI}}_t;\ \overline{\mathrm{DPI}}_t)$, the covariance matrix $\boldsymbol{\Sigma}_{Wt}$, and the samples of T_t^2, which define the state of control reference for each period t.

An ex post facto analysis of the actual project execution was conducted. In this phase, at any t, only an individual vector $\mathbf{W}_t = (\mathrm{CPI}_t, \mathrm{DPI}_t)$ is available. Fig. 10 shows the control ellipse for the simultaneous monitoring of the project duration and cost progress in two review periods (80 and 240 days) with the fixed arbitrary thresholds (0.9 and 1.1) generally used in project control (dashed line) and the empirical upper and lower probability control limits. The periodic observation of the actual performance of the project in periods of 80 and 240 days are also plotted (♦). Fig. 10 indicates that the ability to distinguish between acceptable and unacceptable variations can be improved when the proposed statistical approach with the control limits obtained using simulations is used instead of the intuitive fixed thresholds based on practical experience. Additionally, Fig. 10 shows that the in-control ellipse to simultaneously monitor project duration and cost can capture deviations in both dimensions.

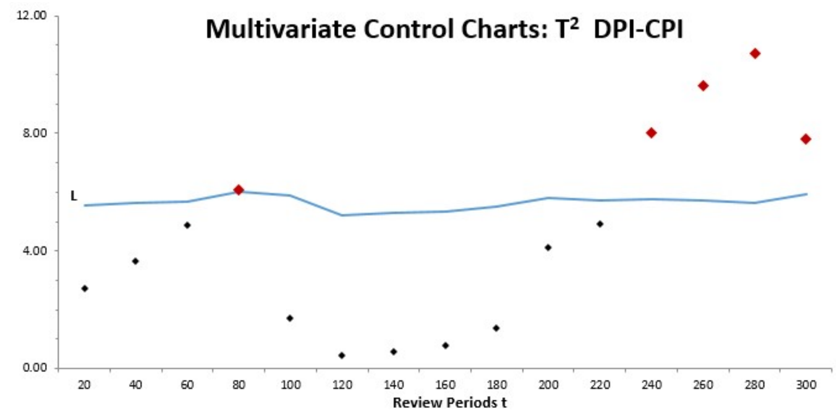
Fig. 10: Control ellipse for the simultaneous monitoring of project duration and cost progress: t=80; t=240 days



Source: Votto et al. (2020b)

Paper #4 pointed out the loss of the temporal sequence of the data as one disadvantage associated with the use of the control ellipse as a single monitoring procedure. It is even more relevant in the project environment, in which the sample of indicators and reference of state of control vary for each review period. This would require drawing an ellipse chart for each period. To overcome this limitation, Paper #4 proposed plotting the periodic observations of T_t^2 in a multivariate control chart with an upper control limit for each *t*. Fig. 11 shows the ex post facto T_t^2 observations of the actual project execution, using $\mathbf{W}_t^0 = (\mathrm{DPI}_t, \mathrm{CPI}_t)$ for each time increment t. An observation higher than the control limit should be considered a warning signal that indicate the presence of special sources of variation, interpreted as an evidence of actual risk of the project delays or cost overrun.

Fig. 11: **T²** Multivariate control chart for simultaneous monitoring of project duration and cost progress



Source: Votto et al. (2020b)

For a more comprehensive analysis, a second Monte Carlo experiment was performed. Different out-of-control scenarios of project executions were generated to investigate the discriminative power of the proposed multivariate approach to differentiate between random and special causes of variation in the project duration and cost. In this phase, the activity duration and cost can exhibit unacceptable variation, larger than the planned variability. The aim was to assess the performance of the proposed multivariate control chart $\mathbf{W}_t^0 = (\mathrm{DPI}_{0t}, \mathrm{CPI}_{0t})$and compare it with the traditional univariate and other T² multivariate control charts built with other variables. For this purpose, it was considered three variations in the activity duration parameters and other three variations in the activity cost parameters, which combined yield a total of nine out-of-control scenarios of the execution phase:

a) Duration 1: Shifts occur only on the parameters $b_{1i} = \delta_{ib} \times \mathrm{b}_{0i}$, $\delta_{ib} = 1.1$;
b) Duration 2: Shifts occur only on $c_{1i} = \delta_{ic} \times \mathrm{c}_{0i}$, $\delta_{ic} = 1.1$;.
c) Duration 3: Shifts occur on $b_{1i} = \delta_{ib} \times \mathrm{b}_{0i}$ and $c_{1i} = \delta_{ic} \times \mathrm{c}_{0i}$, $\delta_{ib} = \delta_{ic} = 1.05$.
d) Cost A: Cost parameters follow the original variability of the planning phase, and the cost shift occurs only because of the linear impact of the duration shift.

e) Cost B: Engineering activities: Coefficient β_{0i} is 0 and the cost Y_i is related to the duration X_i, by a linear function, that is, $Y_i = \beta_{1i}X_i$; Procurement activities: Coefficient β_{i0} follows a uniform distribution function in the range $[\beta_{0i}(1 - \theta_{i0}), \beta_{0i}(1 + \theta_{i0})]$, with $\theta_{i0} = 0.2$; Construction activities: Coefficient β_{0i} follows a triangle distribution ~Tri $(0.9 \times \beta_{0i}, \beta_{0i}, 1.3 \times \beta_{0i})$.
f) Cost C: Coefficient β_{i0} of cost activity i follows a triangle distribution ~Tri $(0.9 \times \beta_{0i}, \beta_{0i}, 1.3 \times \beta_{0i})$.

The first result of the experiment (Table 3) was the higher detection performance and probability of overreaction exhibited by some univariate control charts, particularly the DPI_t individual control chart. This output corresponded with the results of Montgomery (2009) and Ryan (2011), such that even for independent variables, when the same α is used for two or more univariate charts for simultaneously monitoring a process, the true probability of a false alarm increased. In practice, the use of individual control charts in a joint control procedure increases both the detection performance and false alarm rate, measured by the probability of overreaction. This distortion in the joint control procedure can be much more severe, depending on the correlation structure and the number of variables (Kourti and Macgregor, 1996; Montgomery, 2009).

Therefore, although the detection performance of the univariate control charts can be higher, the proposed multivariate control chart exhibited a lower false-positive rate (probability of overreaction) and a significantly higher efficiency. Consequently, the use of the proposed approach can be considered to have dramatically decreased the number of false alarms and increased the efficiency of the project monitoring system in this experiment.

Paper #4 argued that high efficiency is the most important feature once it balances between a high detection performance and a low probability of overreaction. It enables the project team to focus only on the actual deviations and avoid spending unnecessary effort to drill down to the activity level to search for false project problems.

In the proposed experiment, it is possible to note that the T^2 control chart built with $\mathbf{W}_t^0 = (\mathrm{DPI}_t, \mathrm{CPI}_t)$ had the highest efficiency, even when compared with the other T^2 multivariate control charts that combine CPI_t with different schedule performance indexes (TPI_t and SPI_t). This also indicates the potential of the DPI_t to identify deviations.

Therefore, although the proposed approach must be proved under assumptions other than those used in this experiment, this study accomplishes the second research specific objective and highlighted some of its potential benefits to the project control literature. First, the use of only one chart to monitor both the project cost and duration performance, instead of a chart for each dimension, can simplify the project control system. The study demonstrated that the proposed charts can increase the efficiency by detecting actual performance problems and decreasing false alarms. Second, using simulated samples to determine the control limits for each review period support the project team to pre-define a desirable state of control based on the allowable variation of each activity, instead of using historical or progress data to set a fixed control limit for the entire project lifecycle. It also enables the control chart to consider the trend of the expected project variability and in each period.

Table 3: Control charts performance analysis (Paper #4)

Scenario	Chart	Index	Cost A			Cost B			Cost C		
			Detection Performance	Probability Overreaction	Efficiency	Detection Performance	Probability Overreaction	Efficiency	Detection Performance	Probability Overreaction	Efficiency
Duration 1	*Shw*	SPI	0.91	0.47	0.90	0.91	0.48	0.90	0.91	0.47	0.90
	Shw	TPI	0.91	0.47	0.90	0.91	0.48	0.90	0.91	0.47	0.90
	Shw	DPI	**0.96**[a]	0.38	0.92	**0.96**[a]	0.39	0.92	**0.96**[a]	0.38	0.92
	Shw	CPI	0.86	0.40	0.32	0.89	0.50	0.38	0.91	0.47	0.79
	T^2	$\mathbf{W}_t^0$	0.81	**0.27**[a]	**0.94**[a]	0.83	**0.30**[a]	**0.95**[a]	0.86	**0.27**[a]	**0.97**[a]
	T^2	$\mathbf{W}_t^1$	0.88	0.59	0.89	0.86	0.42	0.93	0.85	0.59	0.94
	T^2	$\mathbf{W}_t^2$	0.80	0.34	0.93	0.82	0.36	0.93	0.85	0.36	0.96
	T^2	$\mathbf{W}_t^3$	0.92	0.45	0.92	0.92	0.46	0.92	0.91	0.46	0.96
Duration 2	*Shw*	SPI	0.86	0.52	0.71	0.87	0.50	0.73	0.87	0.51	0.72
	Shw	TPI	0.86	0.52	0.71	0.87	0.50	0.73	0.87	0.51	0.72
	Shw	DPI	**0.92**[a]	0.43	0.76	**0.92**[a]	0.42	0.77	**0.92**[a]	0.43	0.76
	Shw	CPI	0.83	0.32	0.35	0.89	0.45	0.39	0.89	0.42	0.78
	T^2	$\mathbf{W}_t^0$	0.67	**0.24**[a]	**0.84** [a]	0.71	**0.25**[a]	**0.86**[a]	0.75	**0.26**[a]	**0.93**[a]
	T^2	$\mathbf{W}_t^1$	0.75	0.38	0.79	0.77	0.38	0.82	0.81	0.40	0.91
	T^2	$\mathbf{W}_t^2$	0.68	0.30	0.81	0.72	0.31	0.84	0.77	0.32	0.92
	T^2	$\mathbf{W}_t^3$	0.78	0.38	0.80	0.79	0.39	0.82	0.78	0.41	0.90
Duration 3	*Shw*	SPI	0.88	0.50	0.83	0.88	0.50	0.82	0.89	0.50	0.83
	Shw	TPI	0.88	0.50	0.83	0.88	0.50	0.82	0.89	0.50	0.83
	Shw	DPI	**0.94**[a]	0.42	0.86	**0.94** [a]	0.42	0.85	**0.95**[a]	0.42	0.86
	Shw	CPI	0.84	0.38	0.32	0.89	0.48	0.38	0.90	0.44	0.79
	T^2	$\mathbf{W}_t^0$	0.75	**0.25**[a]	**0.91**[a]	0.77	**0.29**[a]	**0.90**[a]	0.81	**0.27**[a]	**0.96**[a]
	T^2	$\mathbf{W}_t^1$	0.79	0.40	0.87	0.82	0.42	0.88	0.85	0.43	0.94
	T^2	$\mathbf{W}_t^2$	0.74	0.32	0.88	0.77	0.35	0.89	0.82	0.35	0.95
	T^2	$\mathbf{W}_t^3$	0.86	0.41	0.87	0.86	0.43	0.88	0.86	0.43	0.94

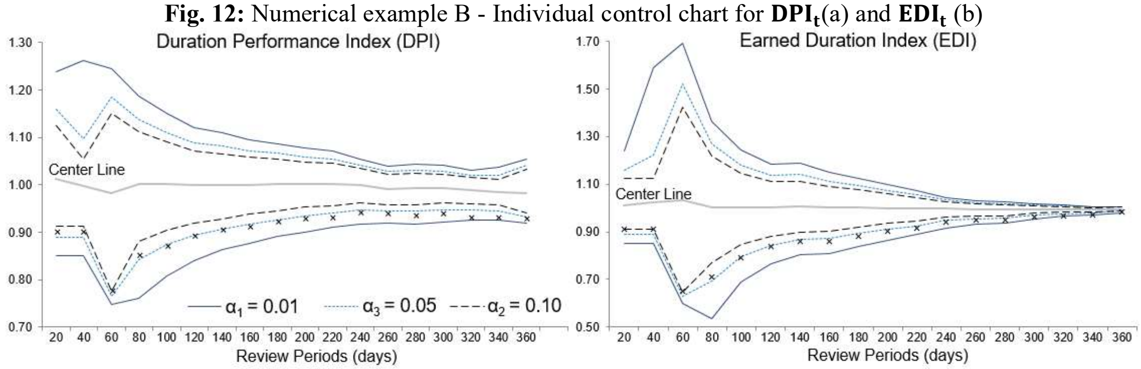
Notes: [a] Duration index with best performance for each scenario
Source: Votto et al. (2020a)

4.3 Specific Objective 3: Define a Decision-Making Process to Set the Most Appropriate Control Limit Width for Project Monitoring

As described in Section 1.2 the third specific objective is to define a decision-making process to define the most appropriate probability control limit width for project monitoring. In order to achieve this objective, Paper #5 incorporated one additional simulation step to determine the most appropriate control limit width for each project, into the previous statistical project control approach using control charts based on simulated samples, to monitor project performance indicators.

Two numerical examples of construction projects are used to illustrate the application of the developed framework to monitor two EDM project performance indicators, the duration performance index (DPI_t), and the earned duration index (EDI_t). The project networks, the PDF parameters of the activity durations, and the project baseline planned durations (μBPD), considering the deterministic planed values are presented in Appendix G. For an extended view of all project details, the reader is referred to Paper #5. For both examples, the procedure in Fig. 8 is followed. Fig. 12 presents the output of the second step, the control charts with different probability control limit width (i.e. α=0.01. α=0.05, and α=0.10), of a biofuel construction project (the numerical example B).

Fig. 12: Numerical example B - Individual control chart for $\mathbf{DPI_t}$(a) and $\mathbf{EDI_t}$ (b)



Source: Paper #5

As described in Section 3.6, in the third step, the goal is to determine the best possible threshold, considering the project targets. For this reason, a new simulation experiment is conducted to measure the ability of the control charts to distinguish between acceptable and unacceptable variations under different control limit widths. To determine this discriminative power of the control charts, additional out-of-control project executions and different project targets, in which each activity duration may exhibit unacceptable variations, are performed.

Tables 4 and 5 present the details and the outputs of the as-planned and two out-of-control simulation scenarios for two different planned durations for the numerical example B and A, respectively.

Table 4: Numerical Example B: Simulation Scenarios – Duration Output

Scenarios	PDF Parameters (Lognormal)	Nrs	μ	σ	Target = 380 days		Target = 390 days	
					On time	Delays	On time	Delays
Planned	μ_{0i} ; σ_{0i}	10,000	378	13.8	61%	39%	68%	18%
Scenario 1.1	μ_{0i} ; $\sigma_{1i} = 3\sigma_{0i}$	10,000	400	44.2	37%	63%	48%	52%
Scenario 1.2	μ_{0i} ; $\sigma_{2i} = 4\sigma_{0i}$	10,000	416	62.7	32%	68%	41%	59%

Source: Paper #5

Table 5: Numerical Example A: Simulation Scenarios – Duration Output

Scenarios	PDF Parameters (Triangular)	Nrs	μ	σ	Target = 315 days		Target = 320 days	
					On time	Delays	On time	Delays
Planned	a_{i0}, c_{i0}, b_{i0}	10,000	312	6.5	68%	32%	90%	10%
Scenario 2.1	$a_{i0}, c_{i0}, b_{i1} = 1.05b_{i0}$	10,000	320	7.8	24%	76%	49%	51%
Scenario 2.2	$a_{i0}, c_{i0}, b_{i2} = 1.10b_{i0}$	10,000	329	9.0	5%	95%	16%	84%

Source: Paper #5

Table 6 presents the performance analysis of the numerical example B. It is important to note that both indicators presented the same performance, despite the different absolute values and control limits of these charts and the tendency of EDI_t to converge to one at the end of the project. This result is similar with the findings about the behaviour of SPI_t and TPI_t, presented in Section 4.1.

Table 6: Control charts performance analysis – Numerical Example B (Paper #5)

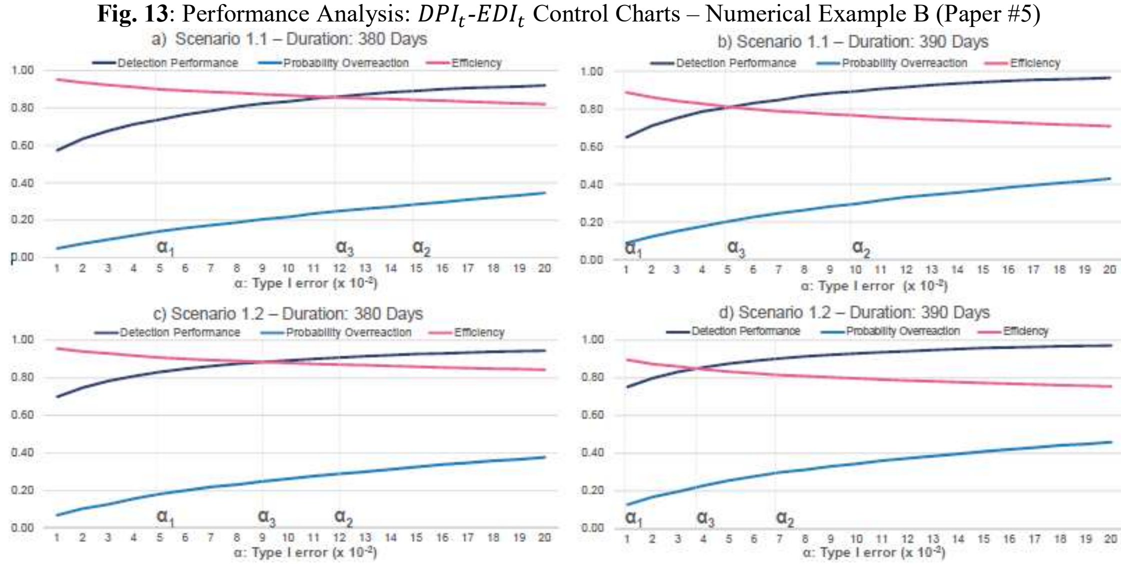
Index	Duration	Index	Type I Error (α)																			
			0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.11	0.12	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.20
$\mathbf{DPI}_t$	380	Detection Performance	0.57	0.64	0.68	0.71	0.74	0.76	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88	0.89	0.90	0.91	0.91	0.91	0.92
		Probability of Overreaction	0.05	0.07	0.10	0.12	0.14	0.16	0.17	0.19	0.21	0.22	0.24	0.25	0.26	0.27	0.29	0.30	0.31	0.32	0.33	0.35
		Efficiency	0.95	0.94	0.92	0.91	0.90	0.89	0.89	0.88	0.87	0.87	0.86	0.86	0.85	0.85	0.84	0.84	0.83	0.83	0.82	0.82
	390	Detection Performance	0.65	0.71	0.75	0.79	0.81	0.83	0.85	0.87	0.88	0.89	0.91	0.92	0.93	0.94	0.94	0.95	0.95	0.96	0.96	0.97
		Probability of Overreaction	0.09	0.12	0.15	0.18	0.20	0.23	0.25	0.26	0.28	0.30	0.32	0.33	0.34	0.36	0.37	0.38	0.40	0.41	0.42	0.43
		Efficiency	0.89	0.86	0.84	0.83	0.81	0.80	0.79	0.78	0.77	0.77	0.76	0.75	0.74	0.74	0.73	0.73	0.72	0.72	0.71	0.71
$\mathbf{EDI}_t$	380	Detection Performance	0.57	0.64	0.68	0.71	0.74	0.76	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88	0.89	0.90	0.91	0.91	0.91	0.92
		Probability of Overreaction	0.05	0.07	0.10	0.12	0.14	0.16	0.17	0.19	0.21	0.22	0.24	0.25	0.26	0.27	0.29	0.30	0.31	0.32	0.33	0.35
		Efficiency	0.95	0.94	0.92	0.91	0.90	0.89	0.89	0.88	0.87	0.87	0.86	0.86	0.85	0.85	0.84	0.84	0.83	0.83	0.82	0.82
	390	Detection Performance	0.65	0.71	0.75	0.79	0.81	0.83	0.85	0.87	0.88	0.89	0.91	0.92	0.93	0.94	0.94	0.95	0.95	0.96	0.96	0.97
		Probability of Overreaction	0.09	0.12	0.15	0.18	0.20	0.23	0.25	0.26	0.28	0.30	0.32	0.33	0.34	0.36	0.37	0.38	0.40	0.41	0.42	0.43
		Efficiency	0.89	0.86	0.84	0.83	0.81	0.80	0.79	0.78	0.77	0.77	0.76	0.75	0.74	0.74	0.73	0.73	0.72	0.72	0.71	0.71

Source: Paper #5

Fig. 13 and Fig. 14 display the performance analysis and the impact of α on the three performance measures of the two scenarios and the two different planned durations for each numerical example, respectively. They show the behavior of the three measures for different values of α. Observe that, the higher the value of α, the higher is the detection performance. Ideally, the detection performance should be as close to one as possible, meaning that unacceptable deviations will be timely detected and the warning signals will be generated to trigger corrective actions to put the project back on track.

In the same way, the probability of overreaction also increases with higher values of α. Nevertheless, a low probability of overreaction is desirable because it describes how often the project team is warned by the control system when only common cause sources of variation are present. A low value of this measure means that the project team does not need to unnecessarily invest time and effort in drilling down the project WBS to find the variation at the activity level to be confined within the acceptable margins (Colin & Vanhoucke, 2014). This result confirms that there is a trade-off between the control charts' performance and the control effort to investigate the cause of every warning signal. For instance, a control chart with higher detection performance also demands more effort to investigate false alarms, due to the higher probability of overreaction.

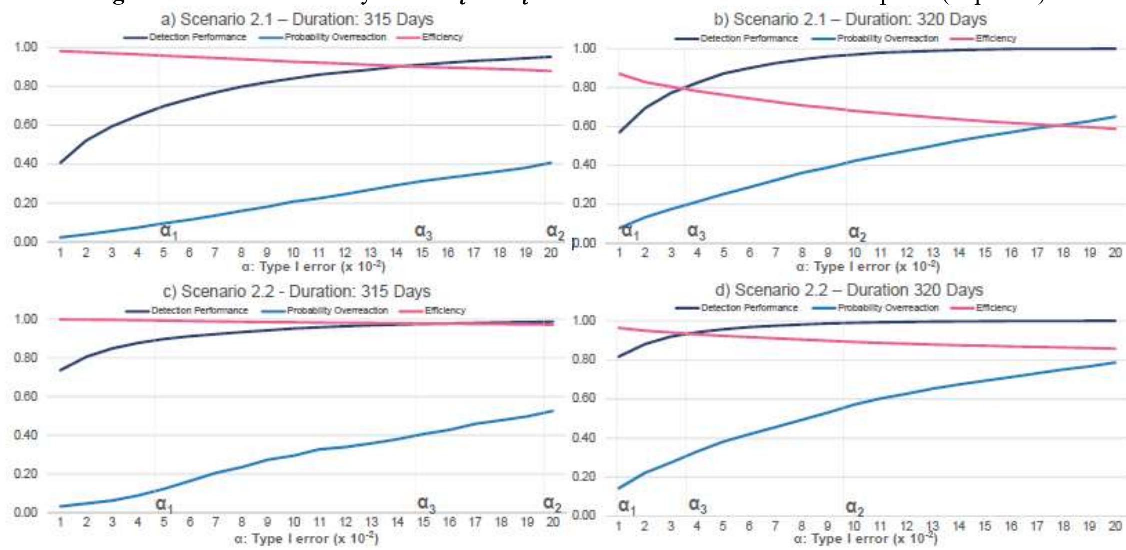
Fig. 13: Performance Analysis: DPI_t-EDI_t Control Charts – Numerical Example B (Paper #5)



Source: Paper #5

To integrate the dynamics of both detection performance and the probability of overreaction, the efficiency shows the probability that the project deadline or budget is exceeded when a warning signal is generated. In opposite to the other two measures, the efficiency of the control chart drops with higher α values. Consequently, a lower α offers a higher control chart efficiency.

Fig. 14: Performance Analysis: $\boldsymbol{DPI_t}$-$\boldsymbol{EDI_t}$ Control Charts – Numerical Example A (Paper #5)



Source: Paper #5

It is important to note that this approach does not aim to define an optimum control limit for a project. Instead, the objective is to support the selection of an appropriated control limit width, depending on different project specific factors. To illustrate the decision the user has to address in this step, examples of three potential values of α are highlighted in each scenario (denoted as α_1, α_2, and α_3 in Fig. 13 and Fig. 14). On the first side, α_1 represents a choice for a higher efficiency compared to the detection performance. For instance, in the example B (Fig. 13), α_1 is set such that efficiency ≈ 0.9, in all different scenarios. Nevertheless, in real life, the user can select α so that the efficiency is even higher. In the other extreme, α_2 is an example of a point in the region where the detection performance is higher than the efficiency. In this case, α_2 is set such that the detection performance ≈ 0.9 in all scenarios but the project team can select values of α targeting a higher detection performance. Finally, α_3 denotes the point in which efficiency and detection performance present the same value.

This finding demonstrates that the appropriate choice of the control limit width depends strongly on the importance of each performance measure to the project team. Their relevance depends on the risk aversion and the willingness to spend effort in investigating potentially false warning signals. Martens and Vanhoucke (2017) and Votto et al. (2020b) stated that in scenarios in which overruns are completely unacceptable and ample resources (in terms of managerial and financial effort) are available to perform a deep investigation drilling down to the activity level, a high detection performance is preferable. In this case, a higher value of α should be chosen (e.g. α_2).

However, if the amount of managerial and financial effort is limited during the project execution, it is better to invest the limited available resources and effort only in periods when the project is truly endangered. Thus, the control charts with the highest efficiency are more valuable (Martens & Vanhoucke, 2017; Votto et al., 2020b). Colin et al. (2015b) showed that a control chart with high efficiency can detect actual performance deviations and, simultaneously, limit false alarms when no deviation in the final project result is observed. Thus, in these cases, a lower value of α (e.g. α_1) is preferable.

If the project team decides to balance these measures, the Type I error can be determined at the point where the detection performance and efficiency cross each other (e.g. α_3). At this point, the control chart presents the same detection performance and efficiency.

Another finding concerns the variation of the control charts performance for different targets relating to the final duration. The numerical examples demonstrated that for longer planned durations (i.e. 390 days in Fig. 13 and 320 days in Fig. 14) and the same level of α, the detection performance and the probability of overreaction are higher, while the efficiency is lower. It means that, depending on the project target duration, a different control limit width should be chosen to have the same control chart performance.

Moreover, in spite of the two numerical examples have confirmed the same behavior of the performance measures for different situations, they demonstrated that the magnitude of the impact of certain decisions are different from project to project. For instance, a smaller shift of the planned duration on the example A generated a greater impact on the control chart's performance compared to the example B. This finding raises the argument that the choice of the appropriate control limits width is project specific and that there is not an optimum level for the control limits regardless some project particular features.

Finally, the last output concerns the performance of the control charts, depending on the probability of project delay. The control charts present better efficiency and detection performance in scenarios with higher probabilities of project delay and larger changes in the project final duration mean than in the ones with lower probability of time overrun due to small changes in the mean of the final duration. These results can be explained because while the Shewhart control charts excel at detecting larger changes in the process mean or variance caused by special sources of variation, their performance decreases in the detection of smaller changes

(Hawkins & Zamba, 2003; Montgomery, 2009). Consequently, different risk analysis scenarios in terms of duration variation would recommend a different decision on the control limit width. For instance, observe that the value of α_3, where the control charts present the same detection performance and efficiency, can change in different simulated scenarios.

With the appropriated probability control limit width defined, it is possible to build the control chart and to monitor the actual project execution by plotting the periodic performance indicators and observing whether they are within the control limits or not.

Despite its limited scope, the proposed method and results accomplish the last specific objective of defining a decision-making process to set the most appropriate control limit width, such that it timely triggers corrective actions only when real deviations are identified and, simultaneously reduces the effort in further investigations of false alarms. The study demonstrated that this choice depends on the project targets, risk and uncertainty scenarios chosen by the team, the project team profile regarding risk aversion or tolerance, and the available resources to investigate any project deviation.

5 CONCLUSIONS

This PhD thesis sought to propose a statistical project control approach to monitor the cost and duration performance of projects. It is a paper-based thesis and its outcomes are five papers, presented in the Part II of this document. The research approach adopted by this work, as well as by its papers, starts with a literature review to investigate the evolution and trends on the application of statistical process control for a project monitoring. Thus, the statistical project control method was constructed by a progressive study in each phase followed by a quantitative research approach, using simulation experiments and single or multi-case studies to illustrate the application and to assess the performance of the method.

5.1 Research Contributions

Previously, Chapter 3 and Chapter 4 presented the main contributions and findings of each research phase and publication. The contribution of each paper is deeper discussed in each paper (see Appendix A - Paper #1, Appendix B - Paper #2, Appendix C - Paper #3, Appendix D - Paper #5, and Appendix E - Paper #5). Based on the findings of these publications, this thesis was able to combine the project management body of knowledge and the SPC literature to provide contributions to an emerging Statistical Project Control field.

In summary, the literature review highlighted the control charts with probability control limits based on simulated samples as a powerful method to set the thresholds to distinguish between acceptable and not acceptable variation on the project performance. However, there were relevant gaps on the existing literature, which was limited to the use of cost-based data to exclusively monitor the duration dimension of project performance. To address such gaps, this work suggested different solutions, using univariate or multivariate approaches, to monitor the cost and duration performance of projects, and proposed a process to set the most appropriated control limit width. Numerical examples were used to illustrate the application on construction projects and simulation experiments results demonstrated that the proposed methods exhibit good performance facilitating the interpretation of actual deviations during project execution, distinguishing between common and special sources of variation.

The major research contributions of the thesis emerge from the papers' results presented in Chapter 4, which are summarized in the following major points. First, using simulated samples to determine the probability control limits supports the project team to pre-define a desirable state of control for each review period based on the allowable variation of each activity, instead of using historical or progress data to set a fixed control limit for the entire project lifecycle.

Second, the use of cost based data to monitor the duration performance of projects has been highlighted as a shortcoming of previous methods. To address this problem, this work proposed the exclusive use of time-based data, from the recently proposed Earned Duration Management (EDM), to monitor the project duration performance using control charts with probability control limits. It demonstrated that the univariate control chart using the new DPI, from EDM, outperformed the traditional SPI and TPI charts in all simulated scenarios (papers #3 and #4). Although further proof under assumptions other than those used in these experiments is necessary, this work highlighted EDM as a promising alternative for project duration control. Furthermore, the use of DPI for duration monitoring brings additional advantages. Different from the more traditional indexes (SPI and TPI), DPI does not use the monetary value of EV in its formula. This makes this index less dependent on the cost dimension that also uses EV to calculate the CPI. Consequently, it ensures the decoupling of both dimensions and a lower correlation between them.

Third, the lack of integration between the duration and cost performance has been identified as a potential weakness in terms of the quality of the feedback provided to the project team. Therefore, a comprehensive project control system must consider the monitoring of both project performance dimensions. In this context, this research proposed to use of such control charts with probability control limits to monitor the cost performance of projects using Earned Value Management (EVM) observations. Furthermore, as a fourth contribution, this research proposed to monitor the duration and cost dimensions simultaneously, using multivariate T^2-type control charts. It was argued that this alternative is preferred, once both dimensions can be correlated and the action to keep one under control can have large consequences on the other. For instance, some decisions to minimize cost overruns can increase the duration of one or more activities. Moreover, the project team can be compelled to spend more effort or money to compensate delays in some activities.

Finally, this research calls attention for the relevant role that the appropriate choice of the control limit width plays to the performance of the control charts for project monitoring. To address this concern, an additional simulation step assesses the performance of the control charts under different targets and scenarios to support the choice an appropriate type I error α. The aim is to set the control limits such that to enable the project team drilling down to lower project levels only when it is really necessary, avoiding investing time and effort to investigate false alarms. It is important to note that this approach does not aim to define an optimum control limit for a project. It is the authors' belief that there is not an optimum control limit width regardless of specific factors, such as the project targets and risk management scenarios. It is clear that only the project team can propose specific scenarios to be simulated in the third step of this method. Instead, the objective is to propose a statistical approach to support the user to select the appropriate control limit width, depending on project targets, risk and uncertainty scenarios estimated by the team, project team profile regarding risk aversion or tolerance, and available resources to investigate any project deviation.

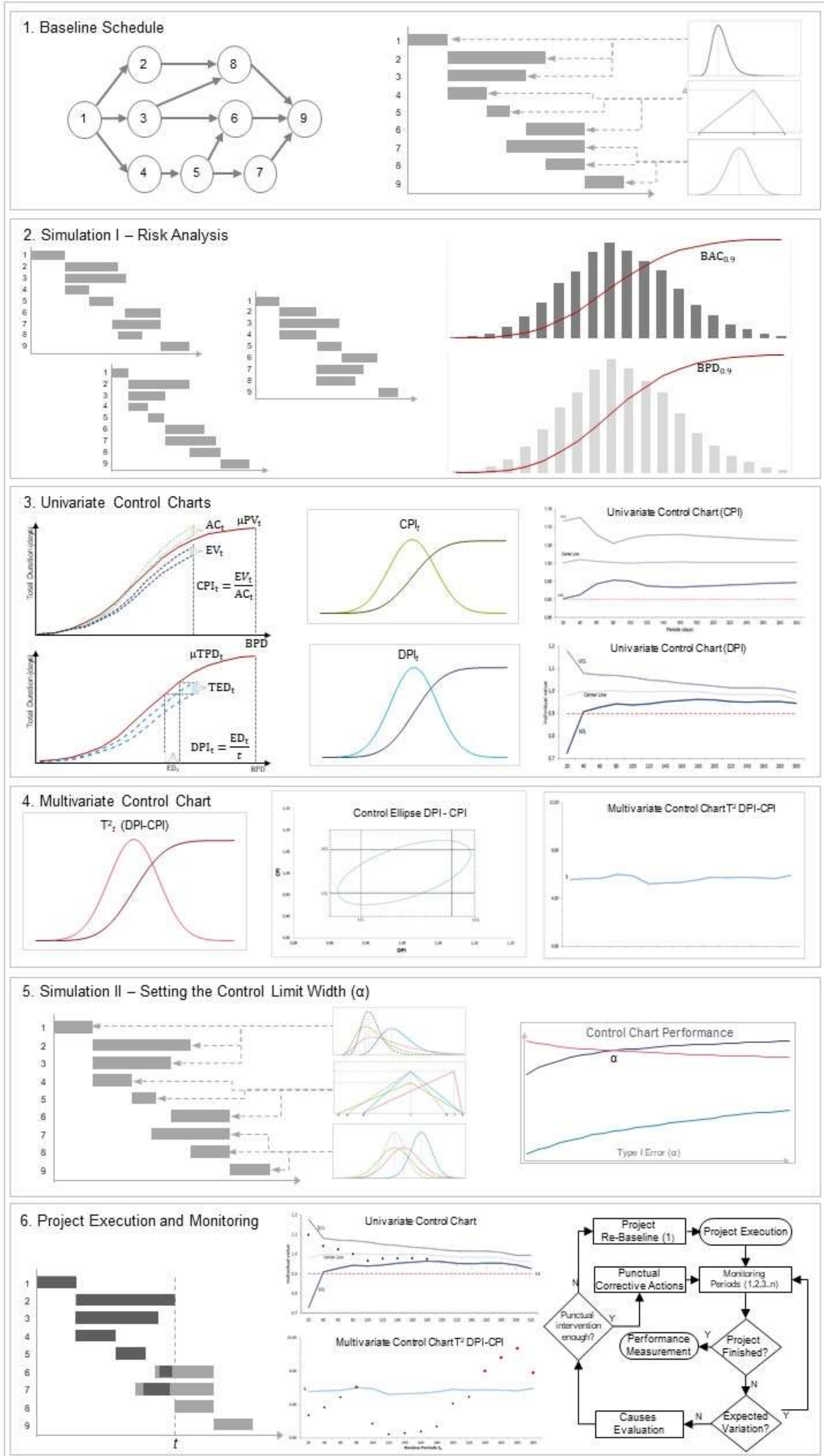
To conclude, the author believes that the results presented in each publication and compiled in this thesis answer the Research Question (Section 1.1): The use of control charts with probability control limits to monitor the duration and cost of projects can improve the ability to distinguish between acceptable and not acceptable variations, and trigger appropriate actions when the observed variation in project's progress exceeds a certain predefined threshold.

5.2 Research Output: Framework for Statistical Project Control

As indicated in Section 1.2, the general objective of this work is to propose statistical project control approach with probability control limits to monitor project performance. Therefore, as the final results of the thesis, Fig. 15 consolidates the approaches presented in the different papers of this thesis and depicts the proposed framework. It is worth noting that the proposed method can be completely or partially used, according to the users' needs.

In the first step, the project network and baseline schedule are defined as a reference point for the subsequent phases. The uncertainty is described by probability distribution functions assigned to produce estimates of each activity duration and cost. It is important to note that different probability distribution functions can be used (e.g. normal, lognormal, uniform, triangular, or beta distributions) to describe the behavior of activity duration. In the second step, the overall project risk is evaluated using a first Monte Carlo simulation. In this step, only the allowable variability for activity duration and costs are used to generate a sample of in-control project execution. The result is used to derive the empirical CDF of the final project duration and cost. This information is the base for an integrated risk analysis to estimate the probability that the project will be completed within a specific date and budget or to predict the most likely end date and budget at completion for different levels of certainty.

Fig. 15: Statistical project control approach



Source: Figure developed by the author for this thesis

In the third step, the periodic values of each indicator are recorded at each time increment *t* and the possible S-curves are generated for each simulated execution. The results are two stochastic S-curves, one for the cost (EV and AC curves) and one for the duration (TED curve). Thus, the periodic values of DPI_t and CPI_t can be calculated for each run and the empirical distribution of each indicator can be obtained for every period, providing the required simulated samples to determine the control limits. It is worth noting that in this approach the probability control limits are not static. Then, for each time increment *t*, new simulated samples are generated, and the control limits are determined and the univariate control charts can be built.

In the fourth step, the multivariate control chart can be built. The in-control empirical CDF of the individual indicators are used to build the empirical distribution of the vector $\mathbf{W}_{0t_k} = (\mathrm{DPI}_{0t}, \mathrm{CPI}_{0t})$. Thus, the mean vector, $\boldsymbol{\mu}_{0\mathrm{W}_{t_k}} = (\overline{\mathrm{DPI}}_{0t}, \overline{\mathrm{CPI}}_{0t})$ and the covariance matrix can be calculated. With this information, it is possible to derive the empirical in-control distribution function of the statistic T_{0t}^2, using expression (12), and to determine the control limits of this chart.

In Step 5, a new simulation experiment can be performed to determine the discriminative power of the control charts. This time, additional out-of-control project executions, in which the activities duration may exhibit unacceptable variation, are simulated. Different out-of-control scenarios can be proposed for the random variation of the activity durations and cost depending on the risk analysis conduct by the project team. Examples of possible scenarios are changes in the standard deviation, the mean, or any other parameter of the distribution function assigned to each activity. The target of this step is to measure the ability of the control chart to distinguish between acceptable and unacceptable variations under different control limit width, defined by a Type I error (α).

The control chart performance is measured according to the generation or not of warning signals for each project execution and identifying whether the simulation run is completed with or without time and cost overruns. Three performance measures are used for this evaluation: the detection performance, the probability of overreactions, and the efficiency. Thus, it is possible to balance different project targets.

It is important to note that there is not an overall recommendation on the adequate level of each performance measure that is worth for every project. There is a trade-off between the performance of the control chart and the control effort to investigate the cause of the warning signals (Colin & Vanhoucke, 2015b). Consequently, it is significant to set the most appropriate control limit width, defined by a type I error (α), such that it allows the trigger of a corrective action only when real deviations are identified and, simultaneously, reduces the effort in further investigations of false alarms.

With the appropriated control limit width defined, it is possible to build the control charts (univariate or multivariate) to monitor the actual project by plotting the periodic performance indicators and observing whether they are within the control limits or not. At any time increment *t*, only one individual observation of each indicator is available ($\mathrm{DPI}_t, \mathrm{CPI}_t$). If the multivariate T2 control chart is used, the statistic T_t^2 can be obtained as the monitored statistic, using expression (13).

The observations that fall within the control region indicate that the project is statistically in control and that only common causes or expected variations are present. In contrast, observations out of the control limits represent warning signals that indicate abnormal project behavior caused by the special variation sources that can influence the expected result. In these situations, the project team must drill down to lower levels of the WBS to thoroughly investigate the cause of variation to determine how to bring the project back on track. It is important to note that a deeper discussion on the corrective actions or contingency plans is not within the scope of this work.

5.3 Limitations and Implication for Theory and Practice

The results presented in this thesis should be interpreted with care as they were obtained from few project examples and present some weaknesses and limitations. Our simulation model assumes that the planned and earned values of activity i ($\mu\mathrm{PV}_{\mathrm{it}}$ and $\mathrm{EV}_{\mathrm{it}}$) follow a linear trend, beginning at zero and reaching the total planned duration upon activity completion. Although it is a common assumption in a project simulation, other models can be tested in future studies.

Another limitation is the use of few network structures owing to the small numbers of case studies. The network structure can be accessed by the serial-parallel (SP) indicator (Vanhoucke et al., 2008) and the real projects presented in the thesis's papers have strong parallel networks (SP ≤ 0.30), which is an important characteristic of the capital goods and construction projects studied in this work. It should be noted that Colin and Vanhoucke (2014) did not observe any significant effect of such SP structures on the performance of statistical project control charts to monitor the performance of projects. Nevertheless, in future studies, different project types with other network structures can be used to verify this approach.

The amount of statistical analysis and computerized methods to generate and analyze the huge amounts of data can be considered a potential weakness of this approach compared to other project control methods. Indeed, this approach assumes a certain shift from the ad-hoc management by experience to a more data-driven management approach, as indicated by Vanhoucke (2019). Nevertheless, it is the believe of the author that, although the proposed approach requires a higher level of maturity to manage projects in such a data-driven way, the main concepts used in the approach (e.g. Monte Carlo simulation and risk analysis) are already used in project control and are well known to the project management community.

Moreover, the EDM methodology has recently received attention in the academic literature and in practical settings. Its benefits over other earned value methodologies, due to its independence from monetary values, has been recognized by several studies. Consequently, it is the author's belief that the EDM calculation will soon be incorporated into commercial project management software packages, what will facilitate the adoption of EDM in the daily project business. Actually, some authors already suggested ways to adapt commercial software to handle EDM calculation (Vanhoucke, 2017).

Therefore, the author hopes that this work can contribute with academic researchers and project management professionals as the developed framework can be utilized in different project environments and practically implemented in real-life projects.

REFERENCES (PART I)

Acebes, F., Pajares, J., Galán, J. M., & López-Paredes, A. (2014). A new approach for project control under uncertainty. Going back to the basics. *International Journal of Project Management*, *32*(3), 423-434.

Acebes, F., Pereda, M., Poza, D., Pajares, J., & Galán, J. M. (2015). Stochastic earned value analysis using Monte Carlo simulation and statistical learning techniques. *International Journal of Project Management*, *33*(7), 1597-1609.

Aliverdi, R., Naeni, L. M., & Salehipour, A. (2013). Monitoring project duration and cost in a construction project by applying statistical quality control charts. *International Journal of Project Management*, *31*(3), 411-423.

Anbari, F. T. (2003). Earned value project management method and extensions. *Project Management Journa*l, *34*(4), 12-23.

Băncescu, M. (2016). Controlling Project Schedule Progress, Using Control Charts. *Cybernetics and Systems*, *47*(7), 602-615.

Batselier, J., & Vanhoucke, M. (2015). Evaluation of deterministic state-of-the-art forecasting approaches for project duration based on earned value management. *International Journal of Project Management., 33(7)*, 1588–1596.

Bauch, G. T., & Chung, C. A. (2001). A statistical project control tool for engineering managers. *Project Management Journal*, *32*(2), 37-44.

Borges Jr, W. F., & Mário, P. D. C. (2017). "Five project-duration control Methods in time units: Case study of a linearly distributed planned value." *J. Constr. Eng. Manage.*, *143(6)*, 05017002.

Chen, Z., Demeulemeester, E., Bai, S., & Guo, Y. (2020). "A Bayesian approach to set the tolerance limits for a statistical project control method". *International Journal of Production Research*, 58(10), 3150-3163.

Colin, J., & Vanhoucke, M. (2014). "Setting tolerance limits for statistical project control using earned value management." *Omega, 49*, 107–122.

Colin, J., & Vanhoucke, M. (2015a). Developing a framework for statistical process control approaches in project management. *International Journal of Project Management*, *33*, 1289-1300.

Colin, J., & Vanhoucke, M. (2015b). A comparison of the performance of various project control methods using earned value management systems. *Expert Systems with Applications*, *42*, 3159-3175.

Colin, J., Martens, A., Vanhoucke, M., & Wauters, M. (2015). A multivariate approach for top-down project control using earned value management. *Decision Support Systems*, *79*, 65-76.

de Andrade, P. A., Martens, A., & Vanhoucke, M. (2019). Using real project schedule data to compare earned schedule and earned duration management project time forecasting capabilities. *Automation in Construction*, 99, 68-78.

El-Din, M. S., Rashed, H. I., & El-Khabeery, M. M. (2006). Statistical process control charts applied to steelmaking quality improvement. *Quality Technology & Quantitative Management*, 3(4), 473-491.

Fleming, Q. W., & Koppelman, J. M. (2005). *Earned value project management,* 3rd Ed. Project Management Institute.

Ghanbari, A., Taghizadeh, H., & Iranzadeh, S. (2017a). Project Duration Performance Measurement by Fuzzy Approach under Uncertainty. *European Journal of Pure and Applied Mathematics*, *10*, 1135-1147.

Ghanbari, A., Taghizadeh, H., & Iranzadeh, S. (2017b). A Fuzzy Approach for Measuring Project Performance Based on Relative Preference Relation. *Industrial Engineering & Management Systems*, *16*, 486-494.

Hadian, H., & Rahimifard, A. (2019). Multivariate statistical control chart and process capability indices for simultaneous monitoring of project duration and cost. *Computers & Industrial Engineering*, *130*, 788-797.

Hammad, M. W., Abbasi, A., & Ryan, M. J. (2018). "Developing a novel framework to manage schedule contingency using theory of constraints and earned schedule method." *Journal of Construction Engineering and Management, 144(4)*, 04018011.

Hawkins, D. M., & Zamba, K. D. (2003). On small shifts in quality control. *Quality Engineering*, *16*(1), 143-149.

Hazır, Ö. (2015). A review of analytical models, approaches and decision support tools in project monitoring and control. *International Journal of Project Management*, *33*(4), 808-815.

Hulett, D. T. (1996). "Schedule risk analysis simplified." *Project Management Network, 10,* 23–30.

Hulett, D. T. (2009). *Practical schedule risk analysis*. Farnham, UK: Gower Publishing, Ltd.

Khamooshi, H., & Golafshani, H. (2014). EDM: Earned Duration Management, a new approach to schedule performance management and measurement. *International Journal of Project Management*, *32*(6), 1019-1041.

Khamooshi, H., & Abdi, A. (2016). Project duration forecasting using earned duration management with exponential smoothing techniques. *Journal of Management in Engineering*, *33*(1), 04016032.

Kourti, T., & MacGregor, J. F. (1996). Multivariate SPC methods for process and product monitoring. *Journal of Quality Technology*, 28(4), 409-428.

Leu, S. S., & Lin, Y. C. (2008). Project performance evaluation based on statistical process control techniques. *Journal of Construction Engineering and Management*, *134*(10), 813-819.

Lipke, W. (2003). Schedule is different. *The Measurable News*, *31(4)*, 31-34.

Lipke, W., Zwikael, O., Henderson, K., & Anbari, F. (2009). Prediction of project outcome: The application of statistical methods to earned value management and earned schedule performance indexes. *International Journal of Project Management*, *27*(4), 400-407.

MacGregor, J. F., & Kourti, T. (1995). Statistical process control of multivariate processes. *Control Engineering Practice*, *3*(3), 403-414.

Martens, A., & Vanhoucke, M. (2017). A buffer control method for top-down project control. *European Journal of Operational Research*, *262*(1), 274-286.

Mestek, O., Pavlík, J., & Suchánek, M. (1994). Multivariate control charts: control charts for calibration curves. *Fresenius' Journal of Analytical Chemistry*, *350*(6), 344-351.

Montgomery, D. C. (2009). *Introduction to statistical quality control*. 6th Ed. John Wiley & Sons.

Mortaji, S. T. H., Noori, S., Noorossana, R., & Bagherpour, M. (2018). *An ex ante control chart for project monitoring using earned duration management observations*. Journal of Industrial Engineering International, 14(4), 793-806.

Pajares, J., & Lopez-Paredes, A. (2011). An extension of the EVM analysis for project monitoring: The Cost Control Index and the Schedule Control Index. *International Journal of Project Management*, *29*(5), 615-621.

PMI (2013). *A guide to the project management body of knowledge.* 5th Ed. Project Management Institute.

Ryan, T. P. (2011). *Statistical Methods for Quality Improvement*. John Wiley & Sons.

Salehipour, A., Naeni, L. M., Khanbabaei, R., & Javaheri, A. (2016). Lessons learned from applying the individuals control charts to monitoring autocorrelated project performance data. *Journal of Construction Engineering and Management*, *142*(5), 04015105: 1-15.

Santos-Fernández, E. (2012). *Multivariate Statistical Quality Control Using R* (Vol. 14). Springer Science & Business Media.

Vandevoorde, S., & Vanhoucke, M. (2006). A comparison of different project duration forecasting methods using earned value metrics. *International Journal of Project Management*, 24(4), 289-302.

Vanhoucke, M. (2011). On the dynamic use of project performance and schedule risk information during project tracking. *Omega*, *39(4)*, 416–426.

Vanhoucke, M. (2012). *Project management with dynamic scheduling: baseline scheduling, risk analysis and project control*. 2nd Ed. Springer.

Vanhoucke, M. (2017). Combining EDM and EVM: a proposed simplification for project time and cost management. *Journal of Modern Project Management*, 5(2), 94-107.

Vanhoucke, M. (2019). Tolerance limits for project control: An overview of different approaches. *Computers & Industrial Engineering*; 127, 467-479.

Vanhoucke, M., Andrade, P., Salvaterra, F., & Batselier, J. (2015). Introduction to earned duration. *The Measurable News*, (2), 15-27.

Vanhoucke, M., Coelho J., Debels, D., Maenhout, B., & Tavares, L (2008). An evaluation of the adequacy of project network generators with systematically sampled networks. *European Journal of Operational Research*; 187: 511–24.

Votto, R.G., Lee Ho, L., & Berssaneti, F. (2017). *Controle Estatístico de Projeto: Gráficos de controle no monitoramento do prazo de projetos*. XLIX Simpósio Brasileiro de Pesquisa Operacional. http://www.sbpo2017.iltc.br/pdf/168238.pdf

Votto, R., Ho, L. L., & Berssaneti, F. (2018). *Controle Estatístico de Projetos com Earned Duration Management: Gráficos de Controle no Monitoramento da Duração de Projetos*. XXXVIII Encontro Nacional de Engenharia de Produção. http://www.abepro.org.br/biblioteca/TN_STO_265_523_35818.pdf

Votto, R., Ho, L. L., & Berssaneti, F. (2020). Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring. *Journal of Construction Engineering and Management*, 146(3), 04020001.

Votto, R., Ho, L. L., & Berssaneti, F. (2020). Multivariate control charts using Earned Value and Earned Duration Management observations to monitor project performance. *Computers & Industrial Engineering*, 148, 106691.

Wang, Q., Jiang, N., Gou, L., Che, M., & Zhang, R. (2006). Practical experiences of cost/schedule measure through earned value management and statistical process control. *Lecture Notes in Computer Science*, 3966, 348–354.

Wauters, M., & Vanhoucke, M. (2017). A nearest neighbour extension to project duration forecasting with Artificial Intelligence. *European Journal of Operational Research., 259(3),* 1097–1111.

Willems, L. L., & Vanhoucke, M. (2015). Classification of articles and journals on project control and earned value management. *International Journal of Project Management*, *33*(7), 1610-1634.

Woodall, W. H., & Montgomery, D. C. (1999). Research issues and ideas in statistical process control. *Journal of Quality Technology*, *31*(4), 376-386.

PART II – APPENDEXES

APPENDIX A: Paper #1: Statistical Project Control: Control Charts for Project Duration Monitoring

Congress	XLIX "*Simpósio Brasileiro de Pesquisa Operacional*" (SBPO)
Authors	Rodrigo Votto; Linda Lee Ho; Fernando Berssaneti
Complete reference	Votto, R.G. Lee Ho, L. Berssaneti, F. (2017). *Controle Estatístico de Projeto: Gráficos de controle no monitoramento do prazo de projetos*. XLIX Simpósio Brasileiro de Pesquisa Operacional.
Available	http://www.sbpo2017.iltc.br/pdf/168238.pdf

XLIX Simpósio Brasileiro de Pesquisa Operacional
Blumenau-SC, 27 a 30 de Agosto de 2017.

Controle Estatístico de Projeto: Gráficos de controle no monitoramento do prazo de projetos

Rodrigo Votto
Universidade de São Paulo
Departamento de Engenharia de Produção
Av. Professor Almeida Prado, Travessa 2, 128
rodrigovotto@gmail.com
Linda Lee Ho
Universidade de São Paulo
Departamento de Engenharia de Produção
Av. Professor Almeida Prado, Travessa 2, 128
lindalee@usp.br
Fernando Berssaneti
Universidade de São Paulo
Departamento de Engenharia de Produção
Av. Professor Almeida Prado, Travessa 2, 128
fernando.berssaneti@gmail.com

RESUMO

Este trabalho propõe uma abordagem de controle estatístico de projetos utilizando gráficos de controle para o monitoramento de prazo de projetos. As variáveis monitoradas são os indicadores de desempenho das metodologias *Earned Value Management* (EVM) e *Earned Schedule Management* (ESM).

Esta abordagem contribui para melhorar a capacidade do EVM e ESM em interpretar os desvios dos indicadores de desempenho na execução do projeto e distinguir desvios esperados, quando o projeto está em estado de controle, e desvios não esperados, que devem ser interpretados como uma evidência de risco de atraso do projeto. Para construir os gráficos de controle são atribuídas funções de distribuição de probabilidade para descrever a incerteza da duração das atividades. Os limites de controle dos gráficos propostos foram obtidos através de simulação de Monte Carlo.

PALAVRAS CHAVE: Earned Value, Incerteza, Simulação de Monte Carlo

Tópicos: SIM – Simulação; EST - Estatística

ABSTRACT

This paper proposes a statistical control approach using control charts to monitor the duration of capital goods projects. The monitored variables are the performance indicators from the Earned Value Management (EVM) and Earned Schedule Management (EVM).

This approach contributes to improve the capacity of EVM and ESM to interpret the deviations in a project execution phase distinguishing between the expected deviations, when project is in statistical control, and the unexpected deviations, which can be interpreted as evidence of a real risk of the project delays.

To build the control charts, probability distribution functions are assigned to describe the uncertainty in the activities duration and the control limits determined by Monte Carlo simulation. Numerical examples illustrate the current proposal.

KEYWORDS. Earned Value, Uncertainty, Monte Carlo Simulation

Paper topics: SIM – Simulation; EST – Statistics;

APPENDIX B: Paper #2: Statistical Project Control with Earned Duration Management: Control Charts for Project Duration Monitoring

Congress	XXXVIII *Encontro Nacional de Engenharia de Produção* (ENEGEP).
Authors	Rodrigo Votto; Linda Lee Ho; Fernando Berssaneti
Complete reference	Votto, R., Ho, L. L., & Berssaneti, F. (2018). *Controle Estatístico de Projetos com Earned Duration Management: Gráficos de Controle no Monitoramento da Duração de Projetos*. XXXVIII Encontro Nacional de Engenharia de Produção.
Available	http://www.abepro.org.br/biblioteca/TN_STO_265_523_35818.pdf

XXXVIII ENCONTRO NACIONAL DE ENGENHARIA DE PRODUCAO
"A Engenharia de Produção e suas contribuições para o desenvolvimento do Brasil"
Maceió, Alagoas, Brasil, 16 a 19 de outubro de 2018.

CONTROLE ESTATÍSTICO DE PROJETOS COM EARNED DURATION MANAGEMENT: GRÁFICOS DE CONTROLE NO MONITORAMENTO DA DURAÇÃO DE PROJETOS

Rodrigo Votto
rodrigovotto@gmail.com
Linda Lee Ho
lindaleeho@gmail.com
Fernando Berssaneti
fernando.berssaneti@gmail.com

2018 enegep

Earned Duration Management (EDM) é a extensão mais recente das metodologias de controle de desempenho de projetos Earned Value Management (EVM) e Earned Schedule Management (ESM). Este trabalho propõe a utilização do indicador de desempenho Duration Performance Index (DPI) da metodologia EDM em uma abordagem de controle estatístico de projetos utilizando gráficos de controle para o monitoramento de prazo de projetos. Serão utilizados gráficos de controle para julgar os desvios de duração durante a execução do projeto e distinguir desvios esperados, quando o projeto está em estado de controle, e desvios não esperados, que devem ser interpretados como uma evidência de risco de atraso do projeto. Para construir os gráficos de controle são atribuídas funções de distribuição de probabilidade para descrever a incerteza da duração das atividades. Os limites de controle do gráfico proposto são obtidos por meio de simulação de Monte Carlo. Um exemplo numérico ilustra a aplicação do método proposto em um projeto de bens de capital por encomenda. Os resultados de experimentos computacionais apontam o DPI como uma alternativa promissora para a medição de desempenho de duração de projetos.

Palavras-chave: Controle Estatístico de Processo, Simulação de Monte Carlo, Gerenciamento de projetos, Earned Value Management, Projetos de bens de capital

APPENDIX C: Paper #3: Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring

Journal	Journal of Construction Engineering and Management
Authors	Rodrigo Votto; Linda Lee Ho; Fernando Berssaneti
Complete reference	Votto, R., Ho, L. L., & Berssaneti, F. (2020). Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring. *Journal of Construction Engineering and Management*, 146(3), 04020001.
DOI	**https://doi.org/10.1061/(ASCE)CO.1943-7862.0001765**

Check for updates

ASCE

Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring

Rodrigo Votto[1]; Linda Lee Ho[2]; and Fernando Berssaneti[3]

Abstract: In this study, earned duration management (EDM) is used as a statistical project control method to monitor the performance of engineering, procurement, and construction (EPC) projects. It represents an extension of the well-known earned value management (EVM) and earned schedule management (ESM) methodologies. In contrast to the latter techniques, which use cost-based data as proxies for assessing the project duration performance, EDM uses time-based metrics for its evaluation. In this method, control charts are employed to monitor deviations during project execution and to identify special sources of variation, interpreted as evidence of real risk of project delays. Monte Carlo simulations are conducted to determine the control limits. The major contribution of this study lies both in the use of control charts with control limits obtained by simulations to monitor the new duration performance index (DPI) in a real EPC project, and in the assessment of its performance compared with that of the traditional EVM and ESM indexes. The results of computational experiments demonstrated generally good performance characteristics of the proposed control charts and suggest that the DPI potentially can be used as a promising metric for monitoring the project duration performance. **DOI: 10.1061/(ASCE)CO.1943-7862.0001765.** © *2020 American Society of Civil Engineers.*

Author keywords: Project performance monitoring; Duration performance index; Control chart; Statistical process control; Monte Carlo simulation.

Introduction

Large projects in the engineer-to-order capital goods industry normally are engineering, procurement and construction (EPC) projects, which can be complex one-of-a-kind product development projects. This type of project increasingly has been adopted in competitive international markets, including 32% of the entire construction sector (Wang et al. 2006; Zhang et al. 2017). However, it faces various challenges due to the high interdependence of activities, phase overlaps, work fragmentation, complex organizational structure, and uncertainty in the prediction of desired outcomes (Yeo and Ning 2002; Yeo and Ning 2006). Therefore, project control represents a major part of project organization aimed at overcoming these challenges. In particular, it evaluates the actual project performance by comparing it with a plan or baseline schedule, measuring ultimate deviations, and taking necessary actions to correct these deviations as early as possible to ensure that the project is completed on time (Acebes et al. 2014; Hazır 2015; Acebes et al. 2015; Willems and Vanhoucke 2015).

A widely used managerial methodology for project performance monitoring is earned value management (EVM), which integrates cost and schedule control in the same framework and provides performance indexes that enable project teams to anticipate cost overruns and project delays (Pajares and López-Paredes 2011; Colin and Vanhoucke 2014; Khamooshi and Golafshani 2014; Acebes et al. 2014, 2015). Initially, EVM focused mainly on costs, but attention gradually shifted to duration control, partially due to Lipke (2003), which introduced the concept of earned schedule management (ESM) (as an extension of EVM) to improve the monitoring of the actual project progress.

Earned duration management (EDM) is the most recent extension of the earned value methodologies. It was originally proposed by Khamooshi and Golafshani (2014) to emphasize the time dimension of projects and to address the shortcomings of EVM and ESM caused by the use of cost-based metrics as proxies for assessing the project duration performance (Vanhoucke et al. 2015). The EDM foundation lies in the exclusive use of time-based data for the generation of progress indicators (Vanhoucke et al. 2015; Ghanbari et al. 2017b). Some studies used EDM as an alternative project progress control technique (Khamooshi and Golafshani 2014; Batselier and Vanhoucke 2015; Ghanbari et al. 2017a, b; Khamooshi and Abdi 2016).

Despite the great success of the earned value methodologies, they often use intuitive thresholds based on the practical experience to distinguish between acceptable and unacceptable variations from the project baseline schedule, which was highlighted as one of the main shortcomings of EVM and its extensions (Colin and Vanhoucke 2014; Colin and Vanhoucke 2015a; Salehipour et al. 2016). To overcome this problem, some studies proposed using control charts to detect abnormal signals by monitoring various EVM performance indexes and thus differentiating between the essential problems and those that do not influence project success (Bauch and Chung 2001; Wang et al. 2006; Leu and Lin 2008;

[1]Ph.D. Student, Departamento de Engenharia de Produção, Universidade de São Paulo, Avenida Professor Almeida Prado, Butantã, São Paulo 05508-070, Brazil (corresponding author). Email: rodrigovotto@gmail.com

[2]Professor, Departamento de Engenharia de Produção, Universidade de São Paulo, Avenida Professor Almeida Prado, Butantã, São Paulo 05508-070, Brazil. ORCID: https://orcid.org/0000-0001-9984-8711. Email: lindalee@usp.br

[3]Professor, Departamento de Engenharia de Produção, Universidade de São Paulo, Avenida Professor Almeida Prado, Butantã, São Paulo 05508-070, Brazil. Email: fernando.berssaneti@usp.br

Note. This manuscript was submitted on February 10, 2019; approved on July 12, 2019; published online on January 2, 2020. Discussion period open until June 2, 2020; separate discussions must be submitted for individual papers. This paper is part of the *Journal of Construction Engineering and Management*, © ASCE, ISSN 0733-9364.

APPENDIX D: Paper #4: Multivariate control charts using Earned Value and Earned Duration Management Observations to Monitor Project Performance

Journal	Computers & Industrial Engineering
Authors	Rodrigo Votto; Linda Lee Ho; Fernando Berssaneti
Complete reference	Votto, R., Ho, L. L., & Berssaneti, F. (2020). Multivariate control charts using Earned Value and Earned Duration Management observations to monitor project performance. *Computers & Industrial Engineering*, 148, 106691.
DOI	https://doi.org/10.1016/j.cie.2020.106691

Computers & Industrial Engineering 148 (2020) 106691

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Multivariate control charts using earned value and earned duration management observations to monitor project performance

Rodrigo Votto *, Linda Lee Ho, Fernando Berssaneti

Departamento de Engenharia de Produção, Universidade de São Paulo, SP, Brazil

ARTICLE INFO

Keywords:
Statistical project control
T^2 control chart
Monte Carlo simulation
Earned duration management

ABSTRACT

This paper presents a statistical project control approach using multivariate T^2 control charts to simultaneously monitor the duration and cost performance of projects. The approach uses the cost performance index, from earned value management, and the duration performance index (DPI) from earned duration management, to build the monitored statistic.

The major contributions of this study are threefold. First, the use of a single chart to monitor both dimensions simplifies the project control system and decreases the false alarms rate. Second, a simulated sample was used to determine the control limits for each review period based on the allowable variation of each activity. Finally, the use of the multivariate approach to monitor the new DPI, which utilizes only time-based metrics, in contrast with more traditional methodologies that use cost-based data as proxies to assess the performance of a project's duration.

The results of computational experiments demonstrate the good efficiency of the proposed T^2 control chart and suggest the new approach is a potentially promising alternative for simultaneously monitoring a project's cost and duration performance.

1. Introduction

The success of projects has been the target of several discussions in the project management literature (Carvalho & Rabechini Junior, 2015; Carvalho, Patah, & de Souza Bido, 2015; Maceta & Berssaneti, 2019). Although the traditional view of project success is a multidimensional construct, it is still associated with fulfilling time, cost, and quality objectives (Gray, 2001; Larson & Gobeli, 1989; Ling, 2004). These dimensions, known as the 'iron triangle', though often criticized, are still considered central to the measurement of project success (Berssaneti & Carvalho, 2015; Papke-Shields, Beise, & Quan, 2010). Bryde, Unterhitzenberger, and Joby (2018) highlighted that two key criteria of project management success are the extent to which the project is delivered on time and within budget.

In this context, this paper focuses on monitoring the performance of the time and cost components of the iron triangle. Project control aims to evaluate the actual progress performance of a project by comparing it with a baseline scheduling and budget and identifying eventual deviations. Warning signals should be generated to trigger the necessary early actions to correct these deviations to ensure that the project is completed on time and within budget (Acebes, Pajares, Galán, & López-Paredes, 2014; Colin & Vanhoucke, 2014; Hazır, 2015; Willems & Vanhoucke, 2015).

Earned value management (EVM) and earned schedule management (ESM) are widely used managerial methodologies to monitor project performance. They provide performance indexes that enable project teams to anticipate project deviations (Acebes, Pajares, Galán, & López-Paredes, 2014; Acebes, Pereda, Poza, Pajares, & Galán, 2015; Colin & Vanhoucke, 2014; Khamooshi & Golafshani, 2014; Pajares & Lopez-Paredes, 2011). More recently, Khamooshi and Golafshani (2014) introduced the earned duration management (EDM) to emphasize the duration dimension of projects and address some shortcomings of EVM and ESM caused by the use of cost-based metrics as proxies to assess the project duration performance (Vanhoucke, Andrade, Salvaterra, & Batselier, 2015; Votto, Lee Ho, & Berssaneti, 2020). Its foundation lies in the exclusive use of time-based data to generate duration indicators (Ghanbari, Taghizadeh, & Iranzadeh, 2017a, 2017b; Vanhoucke, Andrade, Salvaterra, & Batselier, 2015).

Despite the significant success of these methodologies, some of their shortcomings have been highlighted as the decision-making process

* Corresponding author.
E-mail addresses: rodrigovotto@gmail.com, rodrigo.votto@usp.br (R. Votto), lindalee@usp.br (L. Lee Ho), fernando.berssaneti@usp.br (F. Berssaneti).

https://doi.org/10.1016/j.cie.2020.106691
Received 20 September 2019; Received in revised form 1 June 2020; Accepted 22 July 2020
Available online 25 July 2020

APPENDIX E: Paper #5: Earned Duration Management Control Charts: The Relevant Role of the Control Limit Width Definition for Construction Projects Duration Monitoring

Submitted: In Review Process (on January 21st 2021)	
Authors	Rodrigo Votto; Linda Lee Ho; Fernando Berssaneti
Complete reference	Votto, R., Ho, L. L., & Berssaneti, F. Earned Duration Management Control Charts: The Relevant Role of Control Limits Definition for Construction Projects Duration Monitoring.

Journal of Construction Engineering and Management

Earned Duration Management Control Charts: The Relevant Role of the Control Limit Width Definition for Construction Projects Duration Monitoring

--Manuscript Draft--

Manuscript Number:	COENG-10413R1
Full Title:	Earned Duration Management Control Charts: The Relevant Role of the Control Limit Width Definition for Construction Projects Duration Monitoring
Manuscript Region of Origin:	BRAZIL
Article Type:	Technical Paper
Manuscript Classifications:	Project management; Project planning and design; Scheduling
Funding Information:	Conselho Nacional de Desenvolvimento Científico e Tecnológico (301994/2018-8) — Linda Lee Ho
	Conselho Nacional de Desenvolvimento Científico e Tecnológico (421656/2018-2) — Linda Lee Ho
Abstract:	This paper highlights the relevant role that the appropriate definition of probabilistic control limit width plays to the project control and on the performance of the control charts used to monitor the duration of construction projects using Earned Duration Management (EDM) indicators. The design of the control charts is threefold. It refers to the selection of the sample, the sampling interval, and the width of the control limits. The literature on the use of control charts for project monitoring is mainly concerned with the first two parameters and does not dedicate enough attention to how to determine the width of the control limits. Therefore, the main contribution of this paper is to propose a two-step simulation approach to set the most appropriate control limit width, defined by a Type I error (α), depending on different project targets and risk management decisions. The application of the proposed method in two construction projects is presented. Results demonstrate that there is a trade-off between the performance of the control charts and the control effort to investigate the cause of every warning signal. It indicates that the preferable choice of α is strongly influenced by different project duration targets, risk and uncertainty scenarios estimated in the planning phase, and the team's risk profile.
Corresponding Author:	Rodrigo Goulart Votto, Msc. Universidade de Sao Paulo Escola Politecnica São Paulo, SP BRAZIL
Corresponding Author E-Mail:	rodrigovotto@gmail.com
Order of Authors:	Rodrigo Goulart Votto, Msc.
	Linda Lee Ho, PhD
	Fernando Berssaneti, PhD

APPENDIX F: Probability Distribution Functions Used in This Work

F.1. Triangular distribution

A random variable X follows a triangular distribution (i.e. $X\sim Tri\ (a,b,c)$, with parameters a (minimum), b (maximum), and c (most like), if its probability density function (PDF) is:

$$f(x)=\begin{cases} 0\ if\ X<a\ and\ X>\ b \\ \dfrac{2(X-a)}{(b-a)(c-a)}\ if\ a\ \leq X\leq c \\ \dfrac{2(b-X)}{(b-a)(b-c)}\ if\ c\ \leq X\leq b \end{cases}$$

Its cumulative distribution function (CDF) is:

$$F(x)\begin{cases} 0\ if\ x<a\ and\ 1\ if\ X>b \\ \dfrac{(X-a)^2}{(b-a)(c-a)}\ if\ a\ \leq X\leq c \\ 1-\dfrac{(X-b)^2}{(b-a)(b-c)}\ if\ c\ \leq X\leq b \end{cases}$$

Its expected value and variance are respectively:

$$E(X)=\frac{a+b+c}{3},Var(X)=\frac{a^2+b^2+c^2-ab-ac-bc}{18}$$

F.2. Lognormal distribution

A random variable X follows a lognormal distribution (i.e. $X\sim Lognormal\ (\mu,\sigma^2)$) if the logarithm of X is normally distributed with mean μ and variance σ^2 (i.e. $\ln(X)\ \sim N(\mu,\sigma^2)$).

Its probability density function (PDF) is:

$$f(x)=\frac{1}{x\sigma\sqrt{2\pi}}\ exp\left[-\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right]$$

Its cumulative distribution function (CDF) is:

$$F(x)=\Phi\left(\frac{(\ln x)-\mu}{\sigma}\right)$$

where Φ is the CDF of the standard normal distribution (i.e., $N(0,1)$).

Its expected value and variance are respectively:

$$E(X)=exp\left(\mu+\frac{\sigma^2}{2}\right),Var\ (X)=exp(2\mu+\sigma^2)(\exp(\sigma^2)-1)$$

APPENDIX G: Numerical Examples: Project Networks and PDF Parameters

Table G. 1: Numerical Example A: Project Network and PDF Parameters for Activity Durations and Costs

Activity i	Predecessor	DURATION (days)						COST (x 1.000 monetary unit)		
		Min (a)	ML (c)	Max (b)	**μBPDi = (a+b+c) / 3**	σ_{i0}	Inflection	β_{i0}	β_{i1}	**μBPVi (x 1 000)**
1 - Engineering										
2		10	15	20	**15**	2.0	0.5	0	1.0	15
3	2	25	30	35	**30**	2.0	0.5	0	2.5	75
4	2	20	30	40	**30**	4.1	0.5	0	4.5	135
5	3;4	45	55	65	**55**	4.1	0.5	0	4.5	248
6	3	60	70	80	**70**	4.1	0.5	0	7.5	525
7	3	80	90	100	**90**	4.1	0.5	0	3.5	315
8	2	50	70	90	**70**	8.2	0.5	0	10.0	700
9 - Procurement										
10	6	20	25	30	**25**	2.0	0.5	650	0.0	650
11	6	70	85	100	**85**	6.1	0.5	4 200	0.0	4 200
12	7	70	85	100	**85**	6.1	0.5	3 675	0.0	3 675
13	8	70	80	90	**80**	4.1	0.5	7 000	0.0	7 000
14	8	100	110	120	**110**	4.1	0.5	75	0.0	75
15	8	70	80	90	**80**	4.1	0.5	500	14.4	1 652
16	15 ; 13	25	30	35	**30**	2.0	0.5	100	6.0	280
17	16	12	15	18	**15**	1.2	0.5	0	6.0	90
18	2	170	190	210	**190**	8.2	0.5	300	1.8	642
19 –Construction										
20	3	45	55	65	**55**	4.1	0.5	300	4.8	564
21	20	50	60	70	**60**	4.1	0.5	550	5.4	874
22	4	45	55	65	**55**	4.1	0.5	575	6.0	905
23	5;22	80	95	110	**95**	6.1	0.5	675	5.4	1 188
24	21	20	25	30	**25**	2.0	0.5	275	3.6	365
25	24	18	20	22	**20**	0.8	0.5	275	3.6	347
26	21	35	40	45	**40**	2.0	0.5	287	4.8	479
27	24	30	40	50	**40**	4.1	0.5	275	3.0	395
28	10	35	45	55	**45**	4.1	0.5	75	8.0	435
29	24 ; 28	75	85	95	**85**	4.1	0.5	125	9.6	941
30	11 ; 25	75	80	85	**80**	2.0	0.5	100	8.0	740
31	12 ; 27	45	60	75	**60**	6.1	0.5	375	25.0	1 875
32	14 ; 23	12	15	18	**15**	1.2	0.5	0	2.0	30
33	32 ; 17 ; 18	50	60	70	**60**	4.1	0.5	75	7.0	495
34	29 ; 33	12	15	18	**15**	1.2	0.5	0	3.0	45
35	34 ; 30 ; 31	12	15	18	**15**	1.2	0.5	0	3.0	45
36	35	0	0	0	**0**					
TOTAL		μTPD = 1 825 days **μBPD = 300 days**						**μBAC = 30 000**		

Notes: The data is adapted from a real capital equipment EPC project of an industrial plant in South America. In this work, the acceptable variation is modeled using Triangular PDF to estimate the in-control activity durations. Activities 1, 9, 19, and 36 presented are dummy activities without duration and cost and are used only to organize the baseline schedule.

Source: Votto et al. (2020b)

Table G. 2: Numerical Example B: Project Network and PDF Parameters for Activity Durations

Activity i	Predecessor	μ	σ
1		249	3.7
2		51.7	8.3
3	2	200	6.7
4	3;23	65	1.7
5	13;15;4	52	9.1
6	2	50	6.7
7	6	149.2	10.8
8	14	5	0.3
9	2	85	1.0
10	9	83.5	5.1
11	9	100	1.3
12	2	175.2	2.1
13	12;20;10;23	65	11.7
14	2	135	1.5
15	5;7;10;11;23	34.2	5.8
16	2	220	2.9
17	16;23	20.9	1.2
18	2	255	8.3
19	18;17;23	25	1.7
20	9;6	114.2	5.8
21	3	20	0.6
22	4	20.8	1.0
23	10;1	1.7	0.7
TOTAL		μTPD = 2177 days **μBPD = 360 days**	

Notes: The data belong to a biofuel refinery construction project, adapted from an empirical database presented by Batselier and Vanhoucke (2015). In this work, the acceptable variation is modeled using Lognormal PDF to estimate the in-control activity durations.
Source: Paper #5