UNIVERSITY OF PANNONIA

DOCTORAL THESIS

Economic-related Statistical Process Control and Business Process Performance



Author:
Andrew Baah MACCLEVER

Supervisors:
Prof. Dr. Zsolt Tibor KOSZTYÁN
Dr. Attila I. KATONA

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Doctoral School in Management Sciences and Business Administration
Department of Quantitative Methods

November 30, 2026

Economic-related Statistical Process Control and Business Process Performance

Thesis for obtaining a Ph.D. degree in the **Doctoral School in Management Sciences and Business Administration** of the University of Pannonia

in the field of **Social Sciences**
in the subject of **Management and Business Studies**

Written by: Andrew Baah MacClever

Supervisors: Prof. Dr. Zsolt Tibor Kosztyán
Dr. Attila I. Katona

Propose acceptance (yes/no)

.....
Supervisor

As a reviewer, I propose acceptance of the thesis:

Name of reviewer: ..... yes / no

.....
(Reviewer)

Name of reviewer: ..... yes / no

.....
(Reviewer)

The Ph.D. candidate has achieved .....% at the public discussion.

Veszprém, ...
(Chairman of the Committee)

The grade of the Ph.D. Diploma .....

Veszprém, ...
(Chairman of UDHC)

Acknowledgement

First and foremost, I give all glory and thanks to **Almighty God** for His grace, strength, wisdom, protection, and guidance throughout my doctoral journey. The completion of this dissertation would not have been possible without His sustaining presence and blessings.

I am deeply grateful to my **wife and children** for their unwavering love, patience, understanding, encouragement, and support throughout this long and demanding journey. Their sacrifices, especially during periods when my academic responsibilities required considerable time and attention, have been invaluable. They have been a constant source of motivation and strength, and I dedicate a significant part of this achievement to them.

I would like to express my profound gratitude to my supervisors, **Prof. Dr. Zsolt Tibor Kosztyán** and **Dr. Attila I. Katona**, for their academic guidance, constructive criticism, patience, and continuous support throughout my doctoral studies. Their expertise, insightful recommendations, and commitment to the development of my research have significantly shaped this dissertation and contributed to my growth as a researcher.

I am also sincerely grateful to the **members of the Methodology Research Group** at the University of Pannonia for their intellectual support, stimulating discussions, constructive feedback, and collegiality. The opportunity to work and exchange ideas within such a supportive academic environment has enriched my doctoral experience and contributed meaningfully to this research.

My special appreciation goes to my academic mentor, **Prof. Jonathan Annan of Strathmore University Business School, Nairobi, Kenya**, for his mentorship, encouragement, guidance, and continued interest in my academic development. His advice and support have played an important role in shaping my academic and professional journey, and I am sincerely grateful for his contribution to my development as a scholar.

Finally, I extend my sincere appreciation to all those who, in one way or another, contributed to my doctoral journey and to the completion of this dissertation. Although it is not possible to mention everyone by name, I remain deeply grateful for every form of encouragement, assistance, advice, and support I received along the way.

To God be the glory.

UNIVERSITY OF PANNONIA

Abstract

Doctoral School in Management Sciences and Business Administration
Department of Quantitative Methods

Doctor of Philosophy

Economic-related Statistical Process Control and Business Process Performance

by Andrew Baah MacClever

Economic-related Statistical Process Control (ESPC) research remains focused on manufacturing contexts and normal distribution assumptions, leaving service and process-oriented uses largely unaddressed. But this result stems from a systematic literature review that analyzed seventy-one studies using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines data from Web of Science and SCOPUS. The review categorized works by economic models, chart designs, probability distributions, validation techniques, and sectoral applications. Despite its breadth, the analysis uncovered persistent issues such as high analytical demand, narrow modeling constraints, practical barriers to adoption, and scarce accessible datasets. These limitations suggest that current structures are not sufficiently adaptable to diverse operational environments.

Event-Driven Process Chain (EPC) modeling enables real-time monitoring and quality control within business process management systems. The study shows how EPC-based process models support dynamic tracking and validation, traditional control charts fail when applied to business data with skewness. Heavy tails, multimodality, or non-normal patterns, while also, these limitations undermine statistical reliability in such contexts. So the work stresses the necessity of distribution-free methods that preserve validity across varied procedure settings. Such approaches offer greater adaptability to complex operational realities.

For monitoring non-normal operational data, a distribution-free business process control chart is proposed and validated. Simulation studies and a real machine repair process case were used to evaluate its performance. Key metrics included

in-control and out-of-control Average Run Length (ARL), sample-size sensitivity, and shift-detection capability. Results show the method offers stronger robustness and better detection of small-to-moderate shifts compared to standard parametric approaches, in particular in non-normal conditions.

Research finds three major contributions, while theoretically, it applies Statistical Process Control (SPC) principles to business processes by linking economic factors with BPM and nonparametric statistical methods. Methodologically, it offers a hands-on approach for choosing and applying control charts in situations where data does not follow normal distributions. Practically, the results help firms improve quality outcome. But cut process-related expenses, and enable managers to make decisions grounded in data within complex service environments. Together, these elements show that ESPC approaches paired with distribution-free monitoring and business process modeling can boost performance a lot outside standard manufacturing operations.

Abszkrakt

A gazdasági szempontú statisztikai folyamatszabályozással (Economic-related Statistical Process Control, ESPC) kapcsolatos kutatások továbbra is elsősorban a gyártási környezetekre és a normáleloszlás feltételezésére összpontosítanak, miközben a szolgáltatási és folyamatorientált alkalmazások nagyrészt feltáratlanok maradnak. Ezt az eredményt egy szisztematikus irodalmi áttekintés támasztja alá, amely hetvenegy tanulmányt elemzett a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) irányelvei alapján, a Web of Science és a SCOPUS adatbázisokból származó adatok felhasználásával. Az áttekintés a kutatásokat gazdasági modellek, szabályozókártya-konstrukciók, valószínűségi eloszlások, validációs technikák és ágazati alkalmazások szerint kategorizálta. Bár az elemzés széles körű volt, olyan tartós problémákat tárt fel, mint a magas analitikai igény, a szűk modellezési korlátok, a gyakorlati alkalmazás akadályai és a könnyen hozzáférhető adathalmazok hiánya. Ezek a korlátok arra utalnak, hogy a jelenlegi megközelítések nem elég rugalmasak a különböző működési környezetekhez való alkalmazkodáshoz.

Az eseményvezérelt folyamatláncok (Event-Driven Process Chain, EPC) modellezése lehetővé teszi a valós idejű monitorozást és a minőségszabályozást az üzleti folyamatmenedzsment-rendszerekben. A tanulmány bemutatja, hogy az EPC-alapú folyamatmodellek miként támogatják a folyamatok dinamikus nyomon követését és validálását. Ugyanakkor a hagyományos szabályozókártyák nem működnek megfelelően olyan üzleti adatok esetében, amelyek ferdeséget, vastag farkú eloszlást, multimodalitást vagy egyéb nem normális mintázatokat mutatnak. Ezek a korlátok csökkentik a statisztikai megbízhatóságot az ilyen környezetekben. Ezért a kutatás hangsúlyozza az eloszlásfüggetlen módszerek szükségességét, amelyek különböző folyamatkörnyezetekben is megőrzik érvényességüket. Az ilyen megközelítések nagyobb alkalmazkodóképességet biztosítanak az összetett működési környezetekhez.

A nem normális eloszlású működési adatok monitorozására egy eloszlásfüggetlen üzleti folyamat-szabályozókártyát javasoltak és validáltak. A módszer teljesítményét szimulációs vizsgálatokkal, valamint egy valós gépjavítási folyamat esettanulmányával értékelték. A fő teljesítménymutatók közé tartozott a szabályozott és szabályozatlan állapotbeli átlagos futási hossz (Average Run Length, ARL), a mintanagyság iránti érzékenység és az eltolódások detektálási képessége. Az eredmények azt mutatják, hogy a módszer nagyobb robusztusságot és jobb teljesítményt nyújt a kis és közepes mértékű eltolódások felismerésében a hagyományos parametrikus megközelítésekhez képest, különösen nem normális eloszlású adatok esetén.

A kutatás három fő hozzájárulást azonosít. Elméleti szempontból a statisztikai folyamatszabályozás (SPC) elveit alkalmazza az üzleti folyamatokra azáltal, hogy

összekapcsolja a gazdasági tényezőket az üzleti folyamatmenedzsmenttel (BPM) és a nemparametrikus statisztikai módszerekkel. Módszertani szempontból gyakorlati útmutatást nyújt a megfelelő szabályozókártyák kiválasztásához és alkalmazásához olyan helyzetekben, ahol az adatok nem követnek normáleloszlást. Gyakorlati szempontból az eredmények segíthetik a vállalatokat a minőségi teljesítmény javításában, a folyamatokkal kapcsolatos költségek csökkentésében, valamint abban, hogy a vezetők adatvezérelt döntéseket hozzanak összetett szolgáltatási környezetekben. Összességében a kutatás rámutat arra, hogy az ESPC-megközelítések, az eloszlásfüggetlen monitorozási módszerekkel és az üzleti folyamatmodellezéssel kombinálva, jelentősen javíthatják a teljesítményt a hagyományos gyártási környezeteken kívül is.

Contents

1 Introduction **7**

1.1 Motivation of the thesis 7
1.2 Goal of the thesis 9
1.3 Research Questions 10
1.4 Research Proposals 10
1.5 Structure of the thesis 10

2 Background **12**

2.1 Systematic Literature Review Methodology 12
2.1.1 Identification 14
2.1.2 Screening 14
2.1.3 Eligibility 14
2.1.4 Inclusion 15
2.2 Theoretical Foundations of Economic-Related Statistical Process Control (ESPC) 15
2.3 Findings from the Systematic Literature Review 18
2.3.1 Evolution and Classification of ESPC Design Approaches . . 18
2.3.2 Analysis of Methodological Limitations in ESPC Studies . . . 20
2.3.3 Industry Applications and Distributional Assumptions in ESPC Research 24
2.4 Integration of Control Charts in Business Process Management (BPM) 27
2.4.1 Event-Driven Process Chain (EPC) Modeling for Business Processes 29
2.4.2 Traditional Control Charts and Their Dependence on Normality Assumptions 30
2.4.3 Challenges of Non-Normality in Business Process Data 31
2.4.4 Distribution-Free and Nonparametric Control Chart Approaches 32
2.4.5 Performance Evaluation of Control Charts: Sample Size, Shift Detection, and Comparative Analysis 34
2.5 Summary and contribution to literature 35

3 Method **38**
3.1 Business process modeling . . . 39
3.1.1 Business and operation process modeling . . . 39
3.1.2 Formulation of Event-drive Process Chains . . . 41
3.2 Process control . . . 44
3.3 Control charts for business processes . . . 47
3.4 Simulation process . . . 53

4 Case Study **56**

5 Results and Discussion **61**
5.1 Simulation results . . . 61
5.1.1 Distribution fitting and validation . . . 62
5.1.2 In-Control Performance Analysis . . . 63
5.1.3 Out-of-Control Performance Analysis . . . 66
5.2 Results on Real Dataset . . . 70
5.3 Control Chart Selection . . . 73
5.4 Sensitivity Analysis . . . 75
5.5 Chapter Summary . . . 77

6 Summary and Conclusion **79**
6.1 Evaluation of Research Proposals . . . 79
6.1.1 Evaluation of Proposal P1 . . . 79
6.1.2 Evaluation of Proposal P2 . . . 80
6.1.3 Evaluation of Proposal P3 . . . 80
6.2 Contributions to Literature . . . 81
6.2.1 Theoretical Contributions . . . 81
6.2.2 Methodological Contributions . . . 81
6.2.3 Practical Contributions . . . 82
6.3 Managerial Implications and Limitations . . . 82
6.4 Future Research Directions . . . 83
6.5 Summary . . . 84
6.6 Conclusion . . . 85

List of Figures

2.1 PRISMA layout illustrating the data collection and preparation methodology . . . 13
2.2 Evolution of ESPC design types over time: Cumulative number of papers . . . 19
2.3 Proportion of papers by design type . . . 19
2.4 Characteristics of ESPC design types regarding dominant limitations 20
2.5 Frequency of control charts used by industry and distribution type considering ESPC . . . 21
2.6 Frequency distribution of papers by industry type . . . 25
2.7 Frequency of control charts used by industry type considering ESPC 26
2.8 Frequency of control charts used by distribution type considering ESPC 26

3.1 Modeling of a business process, using EPCs (Source: (Kosztyán et al. 2026)) . . . 41
3.2 Schematic figure of an operation process control chart . . . 47
3.3 Steps for fitting control charts . . . 49
3.4 Example of a simulated process shift (Source: (Kosztyán et al. 2026)) 54

4.1 Process flow diagram of the machine repair process. The gray blocks represent the main task groups. . . . 57
4.2 Dispersion of standardized Total Process Time (TPT) values per task. The color of the boxes represents the median of the standardized task durations, the vertical lines represent the range of durations per task, and the black dots denote outliers. . . . 59

5.1 Density plot of real vs. simulated durations . . . 62
5.2 In-control ARL based on the simulation . . . 65
5.3 Out-of-control ARL based on the simulation . . . 68
5.4 Distribution of the TPT . . . 70
5.5 Fitting control charts to monitor the TPT. The black dots represent the sample statistics, the red lines denote the UCL and LCL, and the blue dashed line is the centerline of the chart. . . . 72

5.6 Control chart recommendations for an Operation Process (OP), aiming to minimize ARL_1 74
5.7 Control chart recommendations for an OP, aiming to minimize ARL_1 74
5.8 Control chart recommendations for an OP, aiming to minimize ARL_1 77

6.1 EPC model of the recruitment process in the case of organizational change 92
6.2 Distribution of standardized durations for each task in the recruitment process 93
6.3 Control charts fitted for the recruitment process considering TPT as the control variable 93

List of Tables

2.1 List of questions and possible findings for the proposed TCC 16

4.1 Descriptive statistics for each task in the dataset 58

5.1 Results of the nonparametric statistical tests 63
5.2 Simulation parameters for ARL_0 performance 64
5.3 Control chart parameters during the simulation 64
5.4 Results of the normality tests for different sample sizes 65
5.5 Control chart in-control performances 66
5.6 Simulation parameters for ARL_1 performance 67
5.7 Control chart out-of-control performances 69
5.8 Calculated limits of the fitted control charts 73

6.1 Description of each task in the operational process 90
6.2 Description of each task in the recruitment process 91
6.3 Control chart performances on the human resource recruitment process ($n = 2$) 94
6.5 Summary of the reviewed studies according to economic model, control-chart design and application characteristics. 103

Chapter 1

Introduction

1.1 Motivation of the thesis

Today, businesses are striving in a tough market and are under constant pressure to rationalize their operations at the same time manage the cost element properly. Statistical Process Control (SPC) is a methodology used to measure and control quality in manufacturing processes (Zasadzień and Midor 2018, Mason and Antony 2000), but in recent times, it is considered an effective instrument for monitoring and enhancing business processes. Currently, in SPC, control charts are an indispensable tool utilized globally in businesses for effectively monitoring the production process of high-quality products (Xie et al. 2002). The number of publications on SPC has significantly increased in the last fifty years, reflecting its importance in the context of technological improvement and innovation for increased competitiveness (Lizarelli et al. 2016). Though difficulties in its implementation have been reported including practitioners struggling to grasp the intuitive concepts behind SPC, such as control charts and process variation, highlighting the need for simplified methodologies (Mundwiller 2017), the adoption of SPC has been connected with critical success factors, leading to its acceptance and continued use in industrial settings (Toledo et al. 2017). The use of SPC has also been reported in modern manufacturing processes that aims to reduce waste and ensure high-quality production of discrete parts (Godina et al. 2016). SPC methods, particularly control charts, are widely used in various fields, including manufacturing industries and non-manufacturing industries, such as financial applications like portfolio surveillance and stock trading (Petkov and Ivanova 2024, Bisiotis et al. 2022, Deming 2016).

Systematic Literature Review (SLR) have explored control chart design and monitoring, and there is a limited scope regarding the integration of economic perspective of control chart and its industrial application. For example, Ueda et al. (2022) have explored the use of Multivariate Statistical Process Control (MSPC) charts across

various industries, analyzing their types, applications, and implications. While Peres and Fogliatto (2018) also focused on the integration of variable selection (VS) methods in MSPC. Ho and Case (1994) in their literature review covers various models, approaches, applications, and advancements in the field of economic design of control charts by providing a detailed survey and summary of the work on economic designs of process control charts during a specified period. One other review by Celano (2011) discusses the challenges and recent trends in the economic design of control charts by exploring the application of economic models to establish the parameters of control charts, highlighting the difficulties faced by quality practitioners in implementing these models due to simplifying assumptions and constraints in manufacturing and transactional environments.

Control charts are graphical representations of process data over time and are used to detect when a process is out of control or deviating from its expected performance (Zwetsloot et al. 2024, Sałaciński et al. 2023, Li 2021). Control charts have a rich historical background and have seen recent developments, including their application in fields different from their industrial origins (Aykroyd et al. 2019). Control charts are essential tools for monitoring dynamic processes and rapidly identifying changes in their behavior (Aykroyd et al. 2019, Li 2021). Since the birth of Shewhart chart, various types of control charts have been developed, including x-R, x-s, Cumulative Sum (CUSUM) chart, Exponentially Weighted Moving Average (EWMA) chart, and those with variable sample sizes and control limits, due to its effectiveness for evaluating process stability and also been used in Industry 4.0 for supervising production processes (Sałaciński et al. 2023). Li and Qiu (2020) reveal that traditional control charts face limitations when process assumptions are violated, leading to the development of new charts for nonparametric distributions, serially correlated observations, and small datasets to address unknown process distributions and short-memory dependence. Meanwhile, recent literatures have shown great interest in a new class of nonparametric Shewhart-type control charts which have been introduced, showing competitive in-control and out-of-control performance compared to existing charts (Koutras and Triantafyllou 2018).

In the current dynamic and competitive business landscape, firms in diverse sectors endeavor to enhance their processes in order to attain more efficiency, lower expenses, and enhance customer satisfaction. Although Business Process Modelling (BPM) has traditionally been linked to manufacturing, its principles and methodology can be equally applied and are advantageous to non-manufacturing sectors. This study explores the importance, uses, and advantages of SPC integration with Business Process Management (BPM) in non-manufacturing industries like healthcare, banking, education, retail, etc.

SPC can be used in many areas beyond production processes: healthcare (Thor

et al. 2007), where SPC is used to monitor and improve healthcare processes, such as patient wait times, medication errors, or infection rates; finance (Severin and Schmid 1998), where SPC monitors financial processes, such as transaction processing times, account reconciliation, or fraud detection; software development (Caivano 2005), where SPC controls software development processes, such as code review times, bug fix rates, or testing effectiveness; customer service (Kim and Lim 2021), where SPC improves customer service processes, such as call center wait times, response time to customer inquiries, or customer satisfaction rates; supply chain management (Hajej et al. 2021), where SPC monitor supply chain processes, such as order processing times, inventory levels, or shipping accuracy; education (Bi 2022), where SPC can be used in educational settings to monitor and improve students' performance, teacher effectiveness, or classroom processes; and project management (Colin and Vanhoucke 2015), where SPC controls make span and the project cost to maintain deadlines and project budgets. Nevertheless, to the best of our knowledge, no study exists where SPC is used in businesses or business processes. Despite the many differences between production processes and operation processes, the researcher believes that SPC logic can also be applied to operation processes to improve quality.

1.2 Goal of the thesis

Based on the motivation, the main purpose of this thesis is to explore the use of Economic-related Statistical Process Control (ESPC) methods in business process framework and to design a reliable control chart system for monitoring business processes under real-life data conditions. Traditionally, statistical process control techniques have been used mainly in manufacturing; however, there is a huge potential for their application in business process management that is yet to be realized. Therefore, this research is all about integrating the discussion on ESPC with business process performance measurement.

The first goal of the thesis is to review thoroughly the literature on the existing applications of ESPC to single out the leading design strategies, identify the methodological shortcomings, and the patterns of application in industries. More specifically, the intent is to understand ways in which economic factors have been considered in control chart design and the extent to which these methods have found their way to actual factory floors.

The second goal of the thesis is to determine the extent to which statistical process control methods can still be used in business processes that are represented using business process management notations. Since business process data often violates the standard assumption of normality, I investigate the effectiveness of control charts when they are applied to the data having a non-normal distribution, which is

commonly seen in service and organizational environments.

Lastly, this thesis introduces and tests a distribution-free business process control chart that efficiently detects process shifts in non-normal business process data. Using a series of simulated experiments and real-life examples, I studied the behavior of the newly introduced method in terms of shift-detection ability, sample-size influence, and Average Run Length (ARL) performance. The primary goal is to develop a quality-assurance monitoring method that is both statistically reliable and economically significant, thereby enhancing business process quality and supporting operational decision-making.

1.3 Research Questions

Q_1 : How has economic-related statistical process control (ESPC) chart been considered in real-world industrial processes?

Q_2 : What is the performance of Business Processes (BP) control chart under non-normality conditions compared to traditional control charts?

Q_3 : How does the proposed distribution-free BP control chart perform in detecting process shifts across varying sample sizes and shift sizes in non-normal business processes?

1.4 Research Proposals

P_1 : Economic-related statistical process control (ESPC) charts will be considered mostly in the manufacturing industry compared to the non-manufacturing industries.

P_2 : The performance evaluation of the BP control chart under non-normality conditions reveals its effectiveness in detecting process deviations and facilitating timely corrective actions.

P_3 : The proposed distribution-free BP control chart will demonstrate significantly lower out-of-control Average Run Length (ARL) values compared to traditional parametric charts when detecting small-to-moderate shifts in non-normal processes.

1.5 Structure of the thesis

This thesis is organized into six chapters. Chapter 1 presents the motivation of the thesis, goal of the thesis, research questions, and the research proposals. Chapter

2 introduces the methodology and results of the systematic literature review. This chapter additionally gives an overview about the relevant studies on business processes. The proposed methods are presented in Chapter 3. Chapter 4 presents case studies, while Chapter 5 presents the validation of the results and discussion. Finally, Chapter 6 summarizes my research results and implications.

Chapter 2

Background

This chapter presents a comprehensive review of the literature related to statistical process control applied to business processes. The review is conducted in an organized fashion relevant to the research questions of importance to an ESPC application discussed in Chapter 1.

Initially, an SLR of the literature is performed to analyze the applications of ESPC in industrial real-world contexts (Q1). Secondly, the shortcomings of this empirical research prompts the interest of moving towards business processes environments, where the behaviour of control charts in non-normal states is explored with potential implications to research question 2 (Q2). Lastly, the review of distribution-free and nonparametric control chart approaches set the basis for research question 3 (Q3), namely the behaviour of the introduced control chat in non-normal business process conditions.

2.1 Systematic Literature Review Methodology

In order to answer Research Question 1 (Q1) - *how ESPC charts have been applied in real-world industrial processes* - I conducted a SLR to explore the related studies and review the most relevant researches in the domain of economic-related statistical process control, including classification of the related articles as well. A SLR is useful for locating, selecting, analyzing, appraising and evaluating the articles that are relevant to the study in context.

Following the structure used by Moher et al. (2010), who conducted SLR using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was abducted during data collection and further preprocessing. It directs researchers in conducting a systematic literature review and consists of four basic stages: identification, screening, eligibility, and inclusion. The review was conducted using the web-based tools (i.e. Web of Science and SCOPUS), since they are widely recognized as the most extensive repositories of pee-reviewed journals,

encompassing a wide array of scientific publications (Centobelli et al. 2018). In addition, these databases have been widely utilized in generating systematic literature studies in the domains of control charts (Ueda et al. 2022).

The procedures for the data collection and the preprocessing are shown in Figure 2.1. To select the group of articles to be covered by this review, a series of steps was adopted to ensure appropriate rigor and repeatability. In subsection 2.1.1, 2.1.2, 2.1.3 and 2.1.4, the four stages of the literature search are discussed.

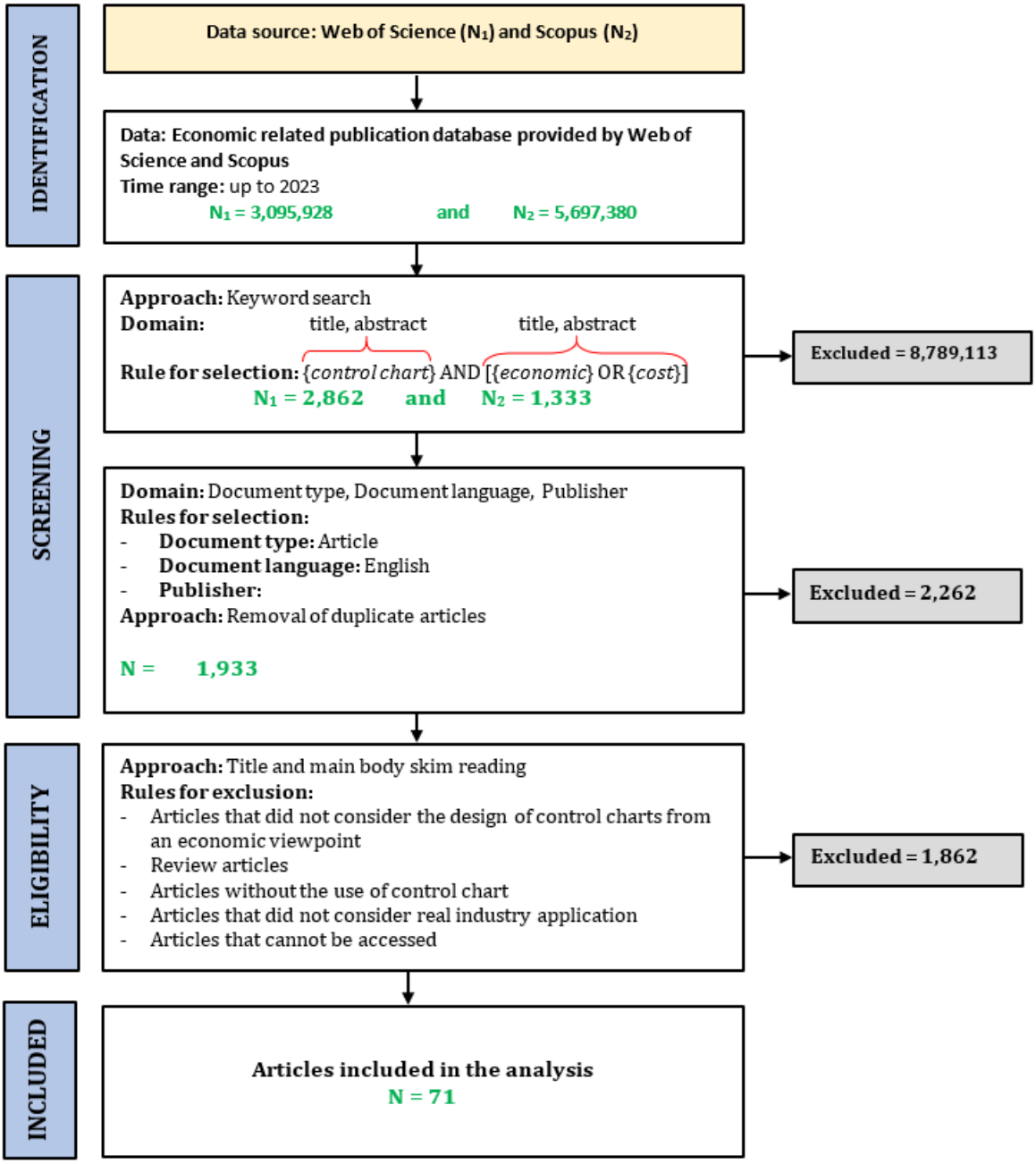


Figure 2.1: PRISMA layout illustrating the data collection and preparation methodology

2.1.1 Identification

The literature search was conducted using two comprehensive, web-based academic databases: Web of Science and SCOPUS (Centobelli et al. 2018). These databases were selected because they are widely recognized as the most extensive repositories of peer-reviewed journals, encompassing a broad array of scientific publications across multiple disciplines (Baas et al. 2020, Centobelli et al. 2018). The keyword search strategy combined controlled terms using Boolena operators (AND, OR) to retrieve relevant articles. The search strings employed were:

- Web of Science: {control chart} AND {economic OR cost}
- SCOPUS: (TITLE-ABS-KEY (control chart)) AND (((TITLE-ABS-KEY (cost) OR TITLE-ABS-KEY (economic))) AND (TITLE-ABS-KEY(control chart)))

The search was restricted to full articles published in English, with publication dates ending in 2024. This generic keyword combination allowed for the retrieval of as many ESPC-related articles as possible while minimizing the risk of excluding relevant publications through overly restrictive search terms.

2.1.2 Screening

Initial screening involved removing duplicate records identified across the two databases through manual cross-checking and spreadsheet verification. Two phases of data screening were established to detect control chart-related publications via keyword search. During this phase, title and abstract reviews were conducted to identify studies directly related to ESPC, cost optimization in control charts, and their industrial applications.

2.1.3 Eligibility

In this stage, manual reading was applied to the remaining articles after execution of the screening stage. Articles were included in the review if they: (1) focused on statistical process control charts and their economic aspects; (2) addressed control chart design, implementation, or monitoring methodologies; (3) discussed cost models or economic models in process control; or (4) presented industrial applications of ESPC. Articles were excluded if they lacked empirical or theoretical contribution to ESPC, were written in languages other than English, or addressed only general statistical methods without specific application to process control.

2.1.4 Inclusion

Full-text review of all remaining articles was conducted to ensure appropriateness for inclusion.

2.2 Theoretical Foundations of Economic-Related Statistical Process Control (ESPC)

In order to put the findings of Q1 into context, it is necessary to establish the theoretical foundations of ESPC. Statistical process control with economic considerations incorporates costs into the classical control chart design. It allows decisions to be made that optimize both the statistical and economic performances.

Seventy-one papers were eventually deemed appropriate for this SLR. Each analyzed paper was categorized according to the following classifications:

- Year of publication
- Title of journal
- Last name of the first author or coauthor
- Theoretical Codification Criterion (TCC)

Table 2.1 shows the question-response set regarding the papers proposing ESPC charts.

Table 2.1: List of questions and possible findings for the proposed TCC

Questions	**Possible Findings**
(I) What economic model is applied in ESPC?	I.1 Duncan's cost model I.2 Lorenzen-Vance cost model I.3 Taguchi's loss function I.4 Banerjee and Rahim cost model I.5 Other economic models
(II) What are the economic-related designs developed?	II.1 Economic design II.2 Economic-statistical design II.3 Risk-based design
(III) What kind of charts are used in the ESPC?	III.1 X-bar III.2 Hotelling's T^2 III.3 EWMA III.4 NP III.5 CUSUM III.6 MA
(IV) What approach is used in the process validation?	IV.1 Monte-Carlo simulation data IV.2 Real-process data IV.3 Case study IV.4 Numerical example with sensitivity analysis
(V) What probability distribution is applied to the chart?	V.1 Normal V.2 Burr V.3 Exponential V.4 Weibull
(VI) To what industries is ESPC applied?	VI.1 Manufacturing(M) VI.2 Service(S)

Economic model applied in ESPC: Control charts are statistical instruments employed to oversee processes and identify deviations from intended conditions. Economic models have been established to incorporate cost considerations into control chart design, emphasizing the reduction of economic losses. *Taguchi's loss function*, formulated by Genichi Taguchi, measures the costs incurred due to deviations from a target value in manufacturing processes (Sauers 1999, Lofthouse 1999). The *Lorenzen-Vance cost model* evaluates expenses related to manufacturing and production processes (Prajapati 2010, Sheu and Yang 2006), whereas *Duncan's cost model* focuses on false alarms and missed detections (Castillo and Montgomery 1996, Chou et al. 2000). *Banerjee and Rahim's cost model* builds upon Duncan's approach by incorporating both internal and external failures (Chen and Yang 2002, Banerjee and Rahim 1987). The *Kosztyan and Katona cost model* incorporates process improvement into economic analysis, accounting for expenses related to accurate acceptance, accurate control, erroneous control, and erroneous acceptance (Kosztyán and Katona 2016, 2018, Katona et al. 2023). Organizations are increasingly recognizing the importance of economic factors in informed decision-making, leading to a notable increase in the incorporation of economic models into control charts.

Development of economic-related designs: Economically related designs are crucial in product development, process optimization, and system engineering. They involve incorporating economic factors into the design process to reduce costs, increase effectiveness, and increase total worth. There are three basic approaches: the *Economic*

Design (ED), *Economic Statistical Design (ESD)*, and *Risk-based Design (RBD)*. The ED is a structured approach that considers the financial consequences of design decisions, aiming to reduce the total cost of ownership. ESD uses statistical tools to optimize the design process, focusing on the financial consequences of different design possibilities. The RBD prioritizes risk discovery and reduction at every stage, preventing costly faults and product safety issues.

Chart types used in the ESPC: Several control chart types have been proposed, including popular traditional charts (e.g., X-bars and Hotelling's T2). A specific kind of statistical tool used to track and manage procedures that directly affect economic performance is the economic-related control chart. When possible challenges are addressed, these charts enable a better informed decision-making process by accounting for the economic costs associated with alternative process outcomes.

Types of process validation of the approach: Preferably, samples for observation (process data) should be gathered from a real process environment. Nevertheless, owing to the substantial data demands of ESPC, particularly for training artificial neural networks (ANNs), synthetic samples have conventionally been produced via the Monte Carlo simulation method.

Type of the chart probability distribution applied: The probability distribution used in Control Charts (CCs), especially for economic variables, is crucial for understanding and managing uncertainties, with the choice being based on the data being analyzed. The typical probability distributions utilized include the normal distribution, Burr distribution, binomial distribution, and gamma distribution.

Types of industries in which ESPC is applied: Approaches that utilize ESPCs are increasingly being used across industries to enhance economic stability, efficiency, and risk mitigation, and their integration into economic management strategies is expected to grow as technology advances. Some key sectors that have been explored in the literature include the automotive, food, chemical, electronics, textile, health, and other sectors, which have been classified into the manufacturing and service industries. The adaptability of ESPC across these industries highlights its importance in improving operational efficiency and quality outcomes.

The preceding section has broadly given a framework of the literature on ESPC, highlighting the main economic modeling, design methodologies, types of control charts, validation methods, probability distributions, and industrial applications revealed by the systematic review. Establishing a conceptual basis for how economic aspects have been incorporated in control chart design and use has come from categorizing the studies selected according to the proposed TCC.

However, this descriptive exposition has helped to delineate the theoretical and methodological setting of ESPC, it still has not shown the existence of patterns, trends, and structural imbalances in the research. Hence, an in-depth analysis is necessary

to reveal the distribution of the studies among design categories, industries, and statistical assumptions, as well as to recognize recurrent challenges and potential directions (Almusaed et al. 2025, Ismail et al. 2024, Raza et al. 2017). I introduce the result of the literature research in the next section, which contains the results of the systematic literature review and provides a quantitative and visual assessment of the evolution, dominance, and characteristics of ESPC research.

2.3 Findings from the Systematic Literature Review

The results of the SLR directly address Q1 by revealing patterns in the application of ESPC across industries, methodologies, and statistical assumptions. Tables, heat maps and dendrograms were used to visualize the quantity of researches in the analyzed fields. In this section, I introduce classification of papers distributed among industry types. Also, I visualizes summary of the control chart types, the industries they are used in, and the probability distributions employed in the reviewed papers.

2.3.1 Evolution and Classification of ESPC Design Approaches

Figures 2.2 and 2.3 shows the result of the systematic literature search I conducted related to CC design types of the publication year.

Since my first research question (Q1) focuses on how ESPC charts are applied in real-world industrial processes, the primary objective of this review was to identify and analyze the most relevant papers that demonstrate practical implementations, industrial use cases, and application patterns of ESPC across different sectors. After the search I categorized the papers using the proposed TCC described by Table 2.1.

Figures 2.2 and 2.3 classifies CC design types into ED, ESD, and RBD on the basis of the publication year. To obtain a better view of the publications, Figure 2.2 and Figure 2.3 were constructed, where Figure 2.2 shows the cumulative number of papers published per design type and Figure 2.3 presents the ratio (or the dominance) of the design types.

It is evident from Figure 2.2 that ED initially had the strongest slope from the year 2000 but the trend gradually slowed down meanwhile ESD got stronger over the years especially from 2010. The RBD made its appearance in 2013 and after that, there has been a slow but steady increase. Figure 2.3 gives a clearer image of the dominance changes over time (non-cumulative). The streamgraph is a representation of dominance, showing that from 2000 through 2021, ED had the most dominant role (blue stream), however, the width of the streams and thus the focus, moved towards the utilization of the ESD design type (red stream) and in 2024, this design type accounted for the highest ratio among the three types.

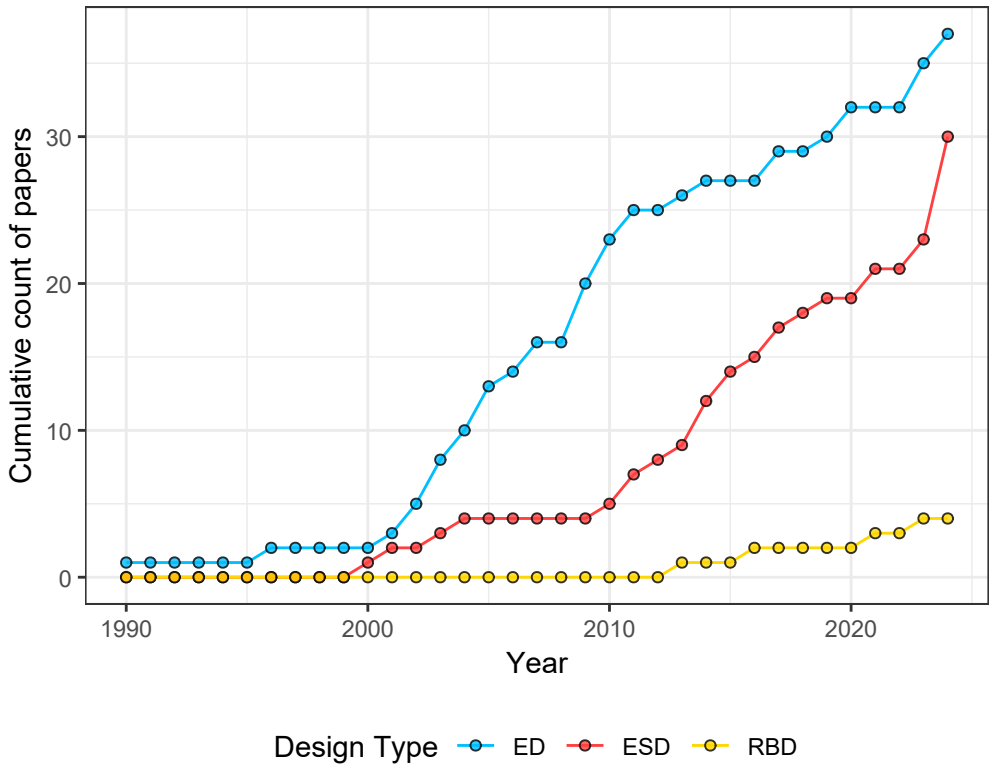


Figure 2.2: Evolution of ESPC design types over time: Cumulative number of papers

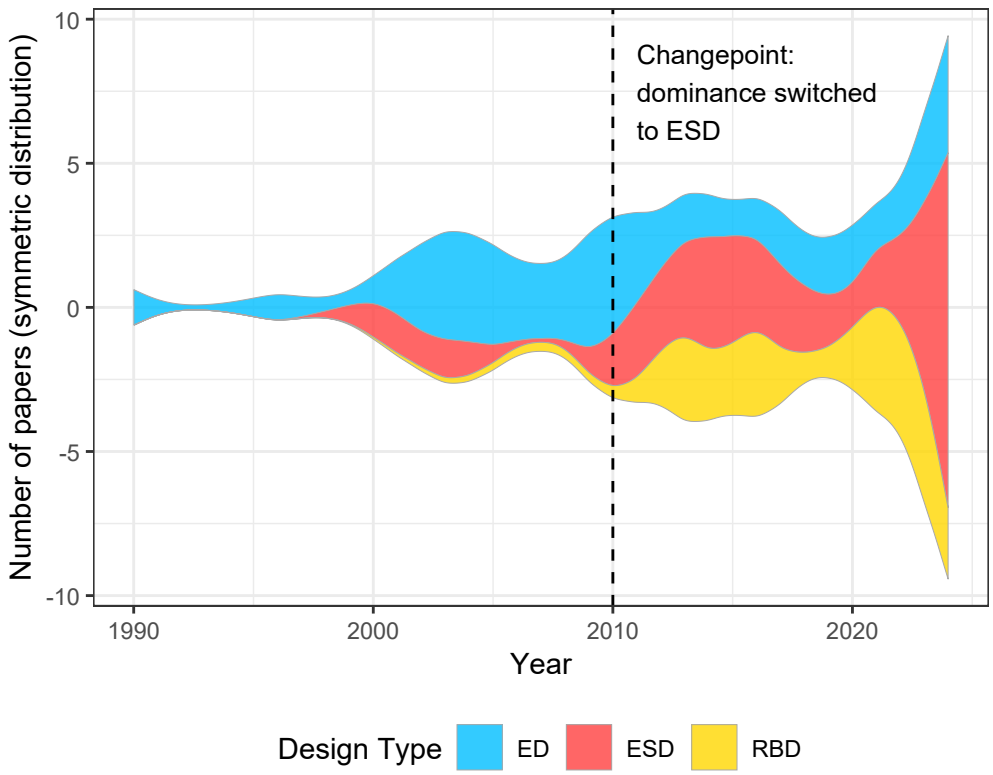


Figure 2.3: Proportion of papers by design type

2.3.2 Analysis of Methodological Limitations in ESPC Studies

Below, Figure 2.4 presents the 71 reviewed papers that have developed various ESPC designs, such as ESD, ED and RBD, and the reported limitations associated with each ESPC design. The ratio of the mentioned limitations is shown in Figure 2.4(a), whereas the number of papers identified for each limitaion per design type is shown in Figure 2.4(b). The limitations that I identified among the related 71 papers were associated with Modeling Assumptions (MA), Parametric Estimation (PE), Analytical Complexity (AC), Limited Data Availability (LA) and Implementation Challenges (IC)

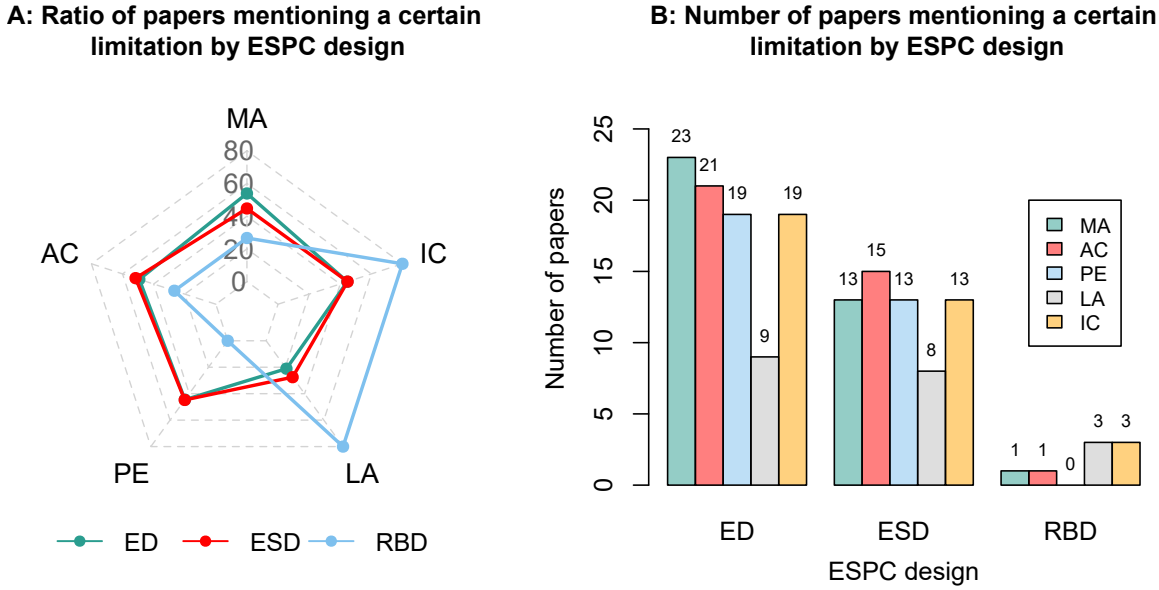


Figure 2.4: Characteristics of ESPC design types regarding dominant limitations

As shown in Figure 2.4(a), the profiles of each design type in terms of limitations are diverse. The limitations of ED and ESD are very similar (red and green lines on the radar chart), and RBD has a much lower ratio in thms of MA, AC, PE but is lacking in IC and LA. This also means that risk-based charts would be very effective in this field if more measurement data were available and if program packages were developed. However, the ratios for RBD are calculated from a small set of papers because this is the newest design type (Figure 2.4) (b)). Limitations and gaps must be analyzed not only from a design-type perspective but also by investigating the differences among different control charts. The limitation profiles per control chart groups are shown in Figure 2.5. To achieve these results, I collected the frequency of the mentions related to each limitation source from the control chart. As a second-stem hierarchical clustering (with Euclidean distance and Ward.D2 method) was used to show the similarities and formulation of groups of control charts with the

same problems/ strengths. The upper section of Figure 2.5 shows the dendrogram, and the lower section shows the radar charts highlighting the ratio of mentions by limitation type. The colors on each radar chart represent the associated control chart, and the black solid line represents the average pattern (centroid of the group).

As is clearly visible on the dendrogram, four different control chart groups can be identified. In the first group (X, s, Taguchi, NP$_x$, EWMA, CUSUM), the most frequently mentioned limitations are IC and AC-related issues. In the second group (T^2, Tukey, t, NP, and moving average), control charts stuggle with mainly PE related difficulties. The second group (p, cause-selecting chart, acceptance chart) struggles mainly with AC issues. The fourth group of control charts (MAX and ARIMA) has the strongest limitations in MA, but they are robust considering the other limitations.

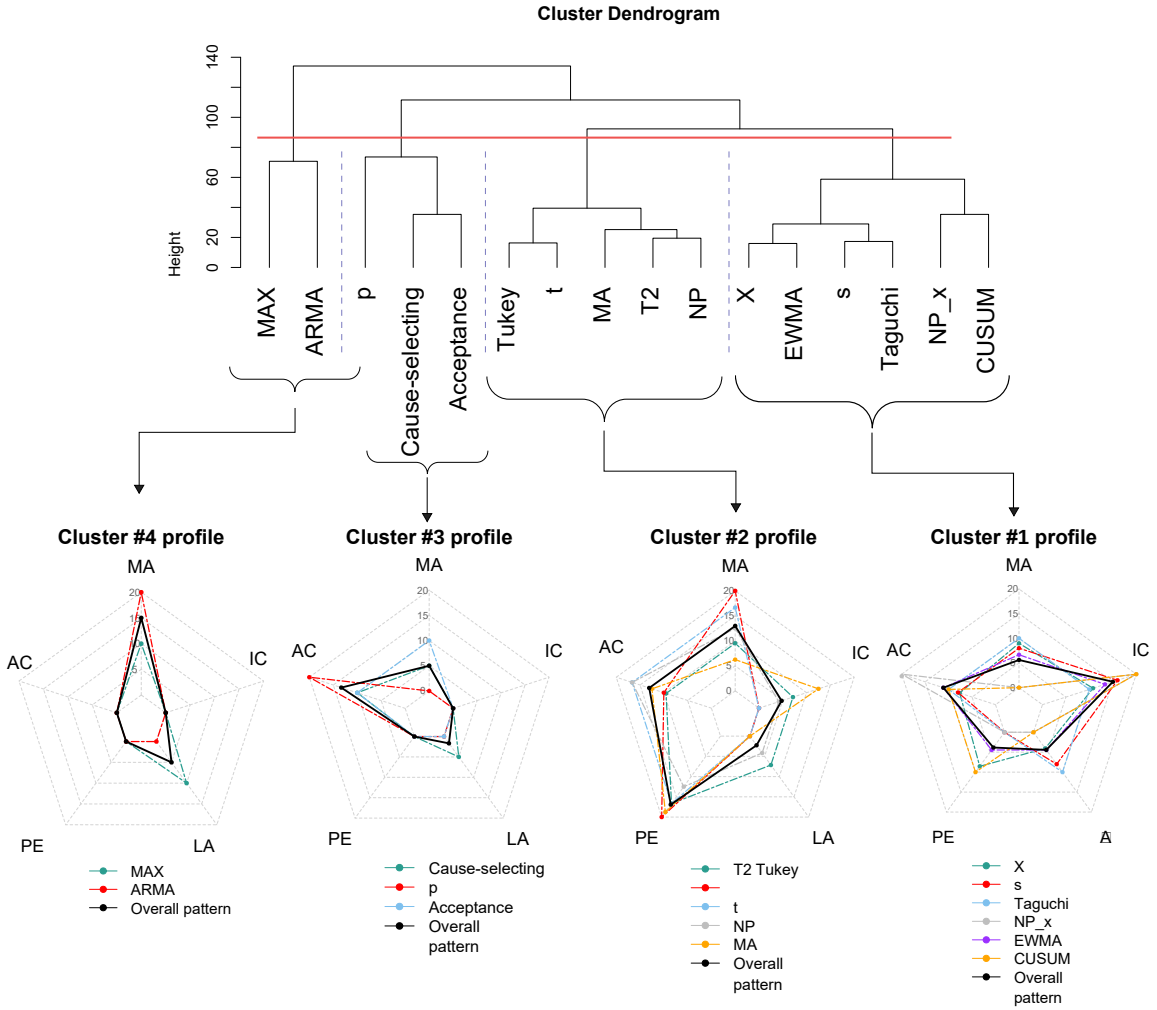


Figure 2.5: Frequency of control charts used by industry and distribution type considering ESPC

The studies identified 13 papers that used the ESD, 23 papers that developed the ED, and a paper that applied the RBD as the ESPC design, encountering *modeling*

assumptions as a limitation. In all, approximately 52.11% of the reviewed papers reported *modeling assumptions* as a limitation. Considering the analytical complexity limitation, 15 papers that used ESD, 21 papers that used ED, and one that employed RBD faced the problem of analytical complexity. This limitation constitutes approximately 52.11% of the papers under review.

In terms of the *parametric estimation* limitation, only 13 papers that employed ESD and 19 papers that employed ED as ESPC designs reported *parametric estimation* as a limitation. The *parametric estimation* in total constituted approximately 45.07% of the papers used in the study design with respect to all the ESPC designs employed in the study.

The availability of data was identified as an issue encountered by some of the academic papers reviewed. The chart shows that 28.17% of the reviewed papers faced the problem of *limited data availability*, including 8 papers that employed ESD and 9 that employed ED and 3 that employed RBD.

The results show that approximately 49.30% of the papers found it difficult to implement the economic study design considered in the studies. Thirteen papers employed ESD faced *implementation challenges*, as did 19 papers employed ED and 3 employed RBD.

Modeling Assumption

A significant number of the studies reviewed acknowledged the limitations associated with the modeling assumptions employed in their economic models and assumed that the characteristics of interest or certain variables in their models have a normal distribution (Koo and Case 1990, Ho et al. 2007, Kooli and Limam 2009, Torng et al. 2009, Celano et al. 2011, Wang and Li 2020); however, this may not always hold true in actual manufacturing processes. Additionally, several studies have assumed simplified scenarios (Chou et al. 2001, Ho and Trindade 2009), which may not accurately encompass the intricacies of actual production processes. The feasibility of process control constraints, such as the control of process parameters or specific control constraints, may be limited in actual scenarios, which in turn limits the capacity of the models to be applied in various manufacturing contexts (Torng et al. 2009). In practical industrial settings, finite sampling periods or restricted sampling intervals may not be suitable. Some studies have concentrated on specific industrial settings or processes (Chen and Yu 2003, Faraz et al. 2010, Nadreri et al. 2019), which limits the generalizability of their findings to other industries. The usefulness of the presented economic models in addressing various monitoring options and CC types.

Analytical Complexity

Analytical complexity, as observed in the current study, refers to the difficulties encountered when numerically optimizing the parameters of the control graph in intricate cost models. Owing to the intricate nature of the problem, researchers frequently resort to approximations or simplified circumstances to make the optimization process more manageable. Mathematical optimization poses challenges for researchers when attempting to optimize CC parameters, including sample sizes, sampling intervals, and action limitations, within complex cost models (Kooli and Limam 2009, Torng et al. 2009). The optimization process encompasses nonlinear functions, many restrictions, and the balancing of diverse cost components. Sophistry-driven cost models consider several elements, such as the costs associated with false alarms, the cost of restoring processes, and the total expenses of monitoring processes (Chen 2003, Yang and Rahim 2005). This complexity adds an additional layer of analytical difficulty, which means that some studies employ approximations or simplifications to help speed up mathematical computations and enhance the manageability of models, thereby potentially sacrificing precision in the process (Yang 2005). To streamline the optimization process, it may be essential to use simplified scenarios. These scenarios may assume specific distributions, constant values, or idealized conditions. Analytical complexity is also present when considering the trade-offs between different cost components and accounting for uncertainty during the optimization process.

Parametric Estimation

Parametric estimation is a common challenge in ESPC designs because of the difficulties in accurately estimating the parameters of statistical distributions, as it helps monitor and improve process performance. The quality and precision of parametric estimation directly influence design parameters, such as sample size, control limits, and sampling intervals. Inaccurate estimation can lead to suboptimal design choices and potentially ineffective CC performance. Parametric estimation is often based on assumptions about the underlying distribution of process data, and deviations from these assumptions or inaccuracies can affect the validity of the chart design. Sensitivity analyses are often conducted to understand how variations in parametric estimation impact the performance and cost-effectiveness of ESPC, assessing the robustness of the designs to uncertainties in parameter estimation.

Limited Data Availability

This constraint pertains to the difficulty of obtaining adequate or comprehensive data to carry out such research or analysis with optimal effectiveness. The limited availability of data can impede the correctness, dependability, and applicability of

the findings and conclusions derived from the study. Obtaining pertinent data can be challenging for researchers, particularly in practical industrial environments, which might affect the reliability and practicality of their proposed models or methods. Researchers encounter difficulties in gathering data, especially in industrial environments, which can be intricate and require a significant amount of time. The lack of sufficient data can impact the ability to apply findings to a wider context, as the results may not accurately reflect real-world phenomena. A lack of appropriate data can undermine the dependability and accuracy of analysis, resulting in potential biases or mistakes. The efficacy and suitability of the presented models may also be constrained by the absence of detailed data. The scarcity of data frequently emphasizes the need for more research and data gathering endeavors to strengthen the reliability and trustworthiness of the conclusions offered in these studies.

Implementation Challenges

Integrating new CCs designs into production systems reveals complex technical and operational challenges . Smooth alignment with existing workflows is key. A shortage of trained staff shows the need for workforce readiness Strong competence in using ESPC. Organizations often resist adopting new methods, reflecting deep-seated opposition to change. And overcoming such resistance calls for building a culture that embraces advance and continuous improvement. This keeps sustainable adoption and long-term success in setup processes.

2.3.3 Industry Applications and Distributional Assumptions in ESPC Research

Figure 2.6 offers interesting observations about how the number of papers are distributed among different industry types. This categorization shows that the applications and importance of ESPC are found in several sectors, which demonstrates the flexibility and efficiency of these control charts in process optimization and improvement of quality management.

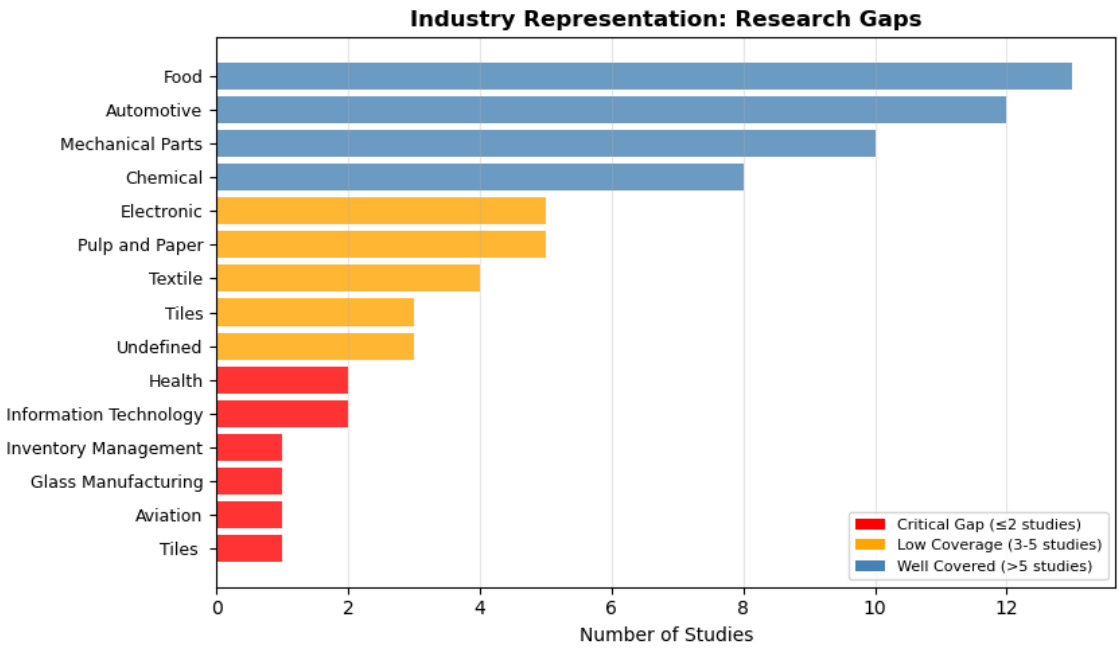


Figure 2.6: Frequency distribution of papers by industry type

The industry most represented was food (thirteen), contributing 18.31% of the total selected articles. The automotive industry contributes 16.90%, whereas the chemical and mechanical parts industries contribute 12.68% and 14.08%, respectively. Other sectors, including electronic, textile, health, pulp and paper, tile, and inventory management, also demonstrate notable engagement with ESPC, highlighting the widespread relevance of these control charts in enhancing quality and economic performance in the manufacturing and service industries.

Figure 2.7 presents a comprehensive summary of the CC types and the industries they are used in, whereas Figure 2.8 presents a summary of the CC types and the probability distributions employed in the reviewed studies. These figures provides a detailed overview of the many applications of ESPC in different industrial sectors and the specific distributions used in each case.

A significant number of industries and CC combinations considered that the process data had a normal distribution (42.3%), followed by Weibull, exponential and burr distributions with 11.3%, 9.9% and 7.0%, respectively; the binomial and multivariate normal distributions were each represented by 5.6%, and the gamma, P-variate normal and Rayleigh distributions were each represented by 2.8%. The other distribution types were considered in only one CC, and the distribution type was not specified in 4.2% of the combinations.

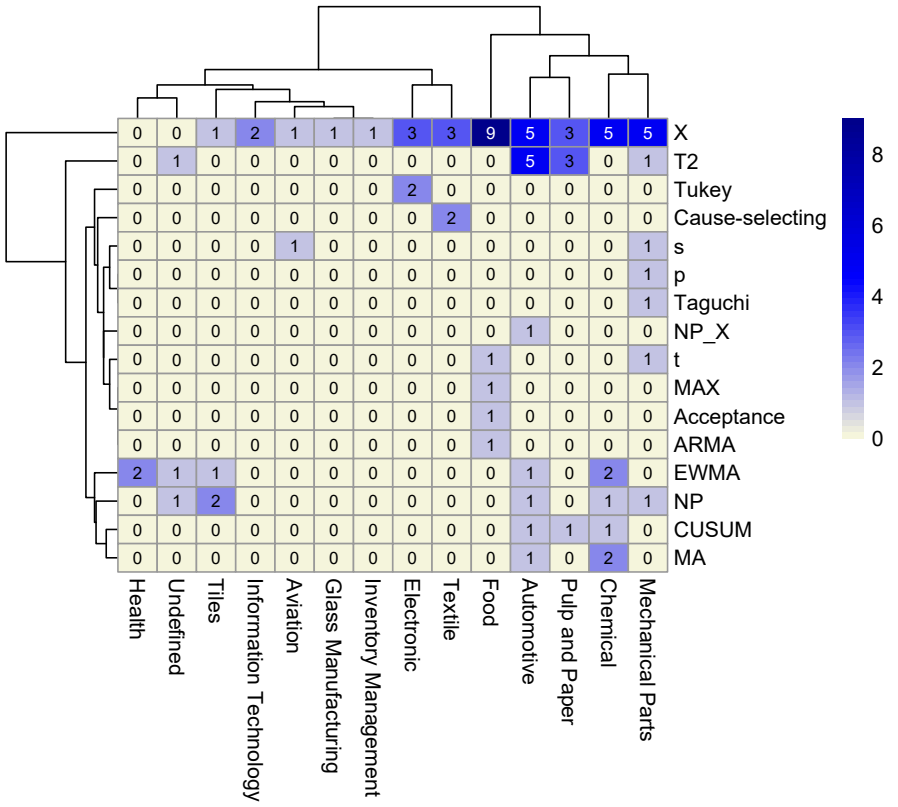


Figure 2.7: Frequency of control charts used by industry type considering ESPC

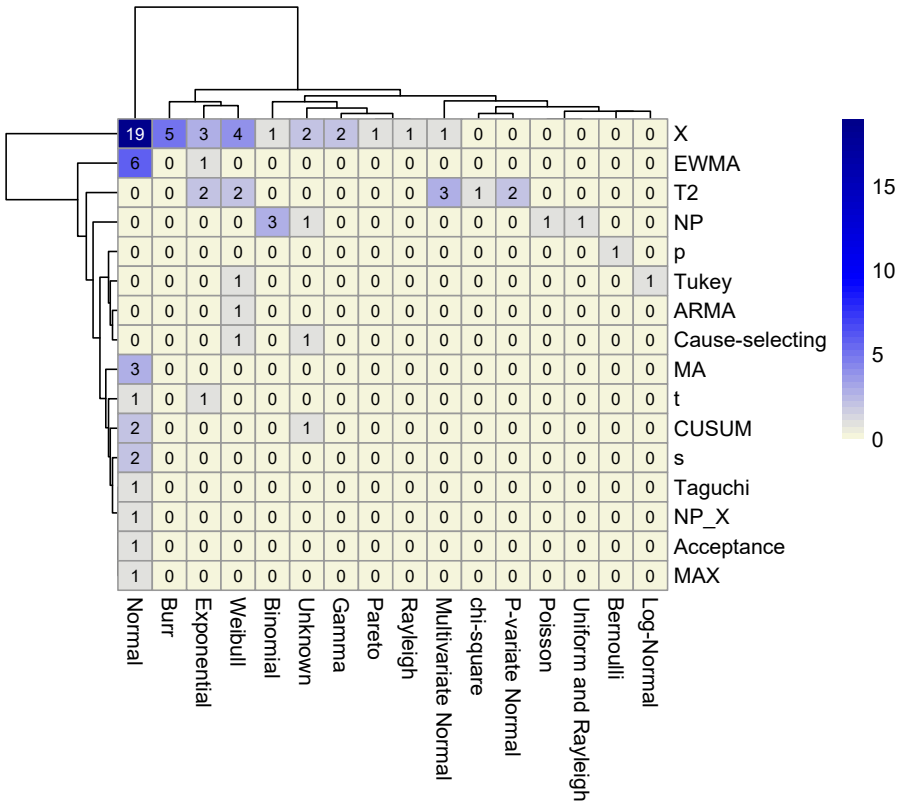


Figure 2.8: Frequency of control charts used by distribution type considering ESPC

The results from a SLR illustrate that research on ESPC has changed significantly over time. This is evident from how different designs have dominated at different times and there are also patterns in the methodological limitations, industrial applications, and distributional assumptions.

The findings show that most ESPC applications are in the manufacturing settings and also that there is still a heavy dependence on parametric assumptions, especially normality. In addition, the recurring challenges concern assumptions in modeling, analytical complexity, and implementation constraints, which together highlight the main gaps in the literature.

It appears that ESPC has become quite established in traditional industrial environments. At the same time, its application in broader organizational contexts, especially business process environments, is still at a very low level. Since service-oriented and knowledge-driven operations are becoming more and more important (Gorgs et al. 2026, Stary 2014, Chew and Gottschalk 2012), Antony and Taner (2003) suggest that researchers should explore ways control chart methodologies could be used within frameworks for business process management frameworks. Thus, the next section departs from industrial ESPC applications and centers its attention on the literature related to BPM and control charts, specifically pointing to event-driven process modeling, issues with non-normality, and the distribution-free monitoring methods.

2.4 Integration of Control Charts in Business Process Management (BPM)

Considering the limited application of ESPC in business processes identified in Research Question 1 (Q1), it is imperative to investigate the potential efficacy of control chart approaches in these contexts. This introduces Research Question 2 (Q2), which pertains to the efficacy of control charts in relation to non-normally distributed business process data.

BPM has emerged as a critical discipline for ensuring operational efficiency and quality in modern organizations. The integration of statistical process control techniques with business process modeling represents a significant advancement in real-time process monitoring and quality assurance (Goecks et al. 2024, Abbasi et al. 2024). Traditional control charts, initially developed for manufacturing environments (Kaya et al. 2025), are increasingly being adapted for business process contexts where process characteristics often deviate from classical statistical assumptions. Event-driven process chains offer a systematic framework for modeling business processes, including the dynamic and sequential characteristics of business activities

(Al-Fedaghi and Makdessi 2020, Amjad et al. 2018a, Minguez et al. 2011, Avila et al. 2021).

The primary difficulty in utilizing control charts for business processes is the reliance on the assumption of normalcy that characterizes most conventional statistical process control techniques (Raza et al. 2024). Empirical business process data tends to be non-normally distributed and are typically characterised by skewness, heavy tails and multimodality, thus they do not meet the assumptions of parametric techniques. In general, if the distributional assumptions are violated, then the false alarm rate will increase and the power of detection will be decreased, especially when standard control charts are used without the required modifications (Abbas et al. 2024b, Muralidharan et al. 2024). Distribution-free or non-parametric methods that are statistically valid irrespective of the underlying process distributions and at the same time are sensitive to the detection of large process changes are gaining more and more attention. Event-Driven Process Chain (EPC) offer a complete modeling framework for illustrating business processes by means of a graphical language that focuses on the flow of events, functions, and logical connections (Wagner 2021, Diba et al. 2020, Amjad et al. 2018a). The EPC method helps to break down highly complicated business processes into easily understandable pieces in a methodical way, thus making it possible to accurately pinpoint the control points for statistical monitoring (Amjad et al. 2018b). This integration creates opportunities for real-time quality control embedded directly within operational workflows, allowing organizations to detect and respond to process deviations before they cascade into significant quality issues or operational disruptions. The synergy between EPC modeling and control chart monitoring provides a comprehensive framework for business process quality management that addresses both structural process design and dynamic performance monitoring (Prasetyaji et al. 2025, Votto et al. 2020).

Research in this domain has increasingly focused on developing robust control chart methodologies that can accommodate the characteristics typical of business process data while maintaining computational feasibility for real-time implementation (Abbas et al. 2024a). This literature review synthesizes current knowledge on the integration of control charts with business process modeling, with particular emphasis on EPC, performance under non-normality conditions, and the comparative effectiveness of distribution-free approaches relative to traditional parametric methods. The analysis addresses critical questions regarding optimal sample sizes, shift detection capabilities, and the practical considerations for implementing these integrated monitoring systems in actual business environments.

2.4.1 Event-Driven Process Chain (EPC) Modeling for Business Processes

EPC represent a semi-formal modeling language that has gained widespread adoption for business process representation and verification. The EPC notation provides a structured approach to documenting business requirements and workflows through a graphical syntax that emphasizes the sequence of events and functions within a process (Amjad et al. 2018a, Avila et al. 2021, Fahland et al. 2020). Unlike purely informal documentation methods, EPCs offer sufficient formality to enable automated analysis and transformation into executable process models, while remaining accessible to business stakeholders who may lack technical modeling expertise (Bazan and Estevez 2020, Angelastro and Ferilli 2020). This balance between formality and usability has contributed to EPC's popularity in enterprise architecture and business process reengineering initiatives (Idogawa et al. 2023, van der Aalst et al. 2024).

The fundamental elements of EPC models include events, functions, and control flow connectors that capture the logical structure of business processes. Events represent states or conditions that trigger process activities, while functions denote the work or transformations performed within the process. Various connector types enable modeling of complex process logic including sequential flows, parallel executions, and conditional branching decisions (Amjad et al. 2018b). Recent extensions to the EPC framework have incorporated capabilities for representing complex event patterns, enabling more sophisticated monitoring scenarios that go beyond simple atomic events. The UMLPACE profile extends EPC expressiveness by adapting Unified Modeling Language (UML) activity diagram concepts to represent both atomic and complex event patterns, facilitating verification of intricate business requirements in real-time systems (Amjad et al. 2018b, Angelastro and Ferilli 2020).

Integration of control charts within EPC-modeled processes requires careful identification of measurement points and quality characteristics to be monitored at each process stage. The event-driven nature of EPCs aligns naturally with trigger-based monitoring approaches, where control chart evaluations occur in response to specific process events rather than at fixed time intervals (van der Aalst et al. 2024). This event-driven monitoring paradigm offers advantages for business processes that exhibit irregular or variable cycle times, as it focuses statistical analysis on actual process completions rather than arbitrary temporal boundaries (Kord Toudeshki et al. 2022, Fahland et al. 2020). Furthermore, the hierarchical decomposition capabilities of EPCs enable multi-level monitoring strategies where aggregate process metrics can be tracked at high organizational levels while detailed operational metrics are monitored at sub-process levels (Avila et al. 2021, Bazan and Estevez 2020).

Transformation of EPC models into formal verification frameworks enables auto-

mated validation of business process properties including correctness, completeness, and consistency (Amjad et al. 2018a, van der Aalst et al. 2024). These transformation capabilities extend to control chart integration, where EPC specifications can be converted into monitoring configurations that define sampling strategies, control limits, and alert mechanisms (Angelastro and Ferilli 2020). The systematic nature of EPC-based process modeling reduces ambiguity in specifying what should be measured, when measurements should occur, and how detected anomalies should trigger process interventions (Idogawa et al. 2023, Bazan and Estevez 2020). Recent research has demonstrated successful application of EPC frameworks in diverse domains including manufacturing process monitoring, service operation management, and supply chain quality control, establishing the versatility of this approach across different business contexts (van der Aalst et al. 2024).

2.4.2 Traditional Control Charts and Their Dependence on Normality Assumptions

Traditional control charts, pioneered by Walter Shewhart in the 1920s, constitute the foundation of statistical process control methodology. The classical Shewhart X-bar and R charts, along with more sophisticated memory-based charts such as EWMA and CUSUM, operate under the fundamental assumption that process data follow a normal distribution (Saeed et al. 2024, Rashid 2022, Teoh et al. 2024). This normality assumption enables straightforward calculation of control limits using simple statistical formulas and allows interpretation of out-of-control signals in terms of standard deviations from the process mean (Knoth et al. 2021, Riaz et al. 2025). Under normality, the probability of false alarms can be precisely controlled through appropriate selection of control limit coefficients, typically set at three standard deviations to achieve an in-control average run length of approximately 370 observations (Haq and Khoo 2020).

The EWMA control chart has emerged as particularly effective for detecting small to moderate process shifts due to its memory-based weighting scheme that assigns exponentially decreasing weights to historical observations (Saeed et al. 2024, Mahmood et al. 2025). The EWMA statistic smooths random variation while remaining sensitive to sustained shifts in the process mean, making it superior to Shewhart charts for gradual drift detection (Knoth et al. 2021). Similarly, CUSUM charts accumulate deviations from the target value and signal when the cumulative sum exceeds threshold boundaries, providing excellent sensitivity to small persistent shifts (Gonzalez and Perry 2025). Both EWMA and CUSUM methodologies rely critically on accurate specification of process parameters and distributional assumptions, with their performance deteriorating markedly when applied to non-normal data (Abbas

et al. 2024a, Haq and Khoo 2020).

Performance evaluation of control charts typically employs run length metrics, particularly the average run length which measures the expected number of samples until a control chart signals. For in-control processes, a large ARL is desirable to minimize false alarms, while small out-of-control ARLs indicate rapid detection of true process changes (Raza et al. 2024, Haq and Khoo 2020). Additional metrics include the standard deviation of run length, median run length, and percentile run lengths, which provide more complete characterization of the run length distribution. These metrics reveal that run length distributions are often highly skewed, particularly for in-control processes, making the median a more interpretable measure than the mean in some contexts (Teoh et al. 2025, 2024).

However, extensive research has documented that traditional control charts exhibit significant performance degradation when applied to non-normal data (Abbas et al. 2024a, Rashid 2022). The in-control ARL may deviate substantially from the nominal value, leading to either excessive false alarms or insufficient sensitivity depending on the nature of distributional departures. Skewed distributions can cause asymmetric performance where the chart responds differently to upward versus downward shifts. Heavy-tailed distributions inflate variance estimates, widening control limits and reducing shift detection capability (Saleh et al. 2024, Gonzalez and Perry 2025). These limitations have motivated development of alternative approaches including transformation methods, parametric charts based on non-normal distributions, and distribution-free methodologies that avoid distributional assumptions entirely (Knoth et al. 2021).

2.4.3 Challenges of Non-Normality in Business Process Data

Business process data frequently exhibit distributional characteristics that violate the normality assumption central to traditional control chart design. Service processes often generate data with exponential or gamma distributions due to the nature of service times and inter-arrival patterns (Dahari et al. 2025, Lu et al. 2025, Shah et al. 2021). Financial processes may produce lognormally distributed data reflecting multiplicative effects or proportional growth mechanisms (Odhiambo et al. 2020, Song et al. 2023). Manufacturing processes involving counts or proportions yield discrete distributions such as binomial or Poisson (John and Subhani 2020, Aslam et al. 2021). Even when individual measurements might approximate normality, aggregated business process metrics combining multiple heterogeneous inputs often result in multimodal or highly skewed distributions that defy simple parametric characterization (Cheng et al. 2024, Zaka et al. 2021).

The impact of non-normality on control chart performance manifests through

multiple mechanisms. First, parameter estimation becomes biased when normal-theory estimators are applied to non-normal data, leading to miscalibrated control limits (Saleh et al. 2024, Rashid 2022). The sample standard deviation, commonly used to estimate process variability, loses efficiency and becomes highly variable when computed from skewed or heavy-tailed distributions (Ali et al. 2020). Second, the distribution of the charting statistic itself deviates from theoretical expectations, altering the false alarm rate and detection probabilities (Fitrianto et al. 2023, Chaudhary et al. 2023). A control chart designed for normality may exhibit in-control ARL substantially different from the nominal value when monitoring non-normal processes, compromising both Type I and Type II error control (John and Subhani 2020).

Skewness introduces particular challenges as it creates asymmetric responses to process shifts. A positively skewed distribution causes traditional control charts to be more sensitive to increases in the process mean than to decreases of equivalent magnitude (Teoh et al. 2025, Zaka et al. 2021). This asymmetry conflicts with the symmetric monitoring philosophy inherent in two-sided control charts and can lead to unbalanced performance across the full range of potential process changes. For business processes where directional shifts have different operational implications, this asymmetric sensitivity represents both a challenge and a potential opportunity if appropriately leveraged through directional monitoring schemes.

Contamination and outliers, common in business process environments due to sporadic exceptional cases or data recording errors, pose additional complications under non-normality (Dahari et al. 2025, Song et al. 2023). Traditional estimators of location and scale are notoriously sensitive to outliers, with even a single extreme value capable of severely distorting control limits. In non-normal distributions, distinguishing genuine outliers from natural heavy-tailed variation becomes problematic, as extreme observations may be consistent with the underlying distribution rather than representing anomalous process conditions. This ambiguity necessitates robust statistical methods that maintain stability in parameter estimation while remaining responsive to meaningful process changes. Robust scale estimators such as the median absolute deviation, Sn, and Qn estimators have been proposed as alternatives to the standard deviation for constructing control limits less susceptible to outlier influence (Adekeye et al. 2021, Gonzalez and Perry 2025).

2.4.4 Distribution-Free and Nonparametric Control Chart Approaches

Distribution-free control charts offer a compelling solution to the non-normality challenges prevalent in business process monitoring by eliminating dependence on specific parametric distributional assumptions. These methodologies, also termed

nonparametric control charts, construct monitoring schemes based on rank-based statistics, sign statistics, or other functionals whose distributions remain invariant across broad classes of continuous distributions (Abbas et al. 2024b, Nimbale and Ghute 2021, Xie and Qiu 2023). The fundamental principle underlying distribution-free methods is to base control limits on the quantiles or order statistics of the monitoring statistic's distribution, which can often be determined exactly or approximated accurately without knowing the underlying process distribution (Gibbons and Chakraborti 2025).

Sign-based control charts represent one prominent category of distribution-free approaches, utilizing the sign of deviations from a target value rather than their magnitudes (Raza et al. 2024, Abid et al. 2024). The sign statistic follows a binomial distribution with known parameters when the process is in control and centered at the target, enabling exact calculation of control limits without distributional assumptions about the original measurements (Montgomery 2020). The nonparametric EWMA-MA sign control chart combines the memory properties of EWMA with moving average smoothing while employing the sign statistic as its basis, achieving sensitivity to small shifts comparable to parametric EWMA charts while maintaining distribution-free properties (Raza et al. 2024, Liu et al. 2021, Oladipupo et al. 2025). Extensions incorporating the Wilcoxon signed-rank statistic retain more information about deviation magnitudes while preserving distribution-free characteristics, offering enhanced power for detecting location shifts (Sofikitou and Koutras 2020).

Recent developments have introduced sophisticated nonparametric charting schemes that incorporate adaptive features and complex weighting structures. The nonparametric adaptive CUSUM chart updates its reference parameter dynamically based on an unbiased estimate of the current process state, enabling effective tracking of processes experiencing time-varying shifts (Abbas et al. 2024b, Xue and Qiu 2021). The homogeneously weighted moving average approach applies uniform weights to recent observations while exponentially downweighting older data, providing an alternative memory structure that demonstrates superior performance for detecting small to moderate shifts in certain scenarios (Aslam et al. 2022). Triple EWMA constructions extend the smoothing concept hierarchically, applying EWMA operations recursively to achieve heightened sensitivity to gradual process drifts (Alevizakos et al. 2021, Gapeev and Stoev 2025).

Performance comparisons consistently demonstrate that well-designed distribution-free control charts achieve out-of-control detection capabilities comparable to or better than traditional parametric charts when processes truly follow assumed parametric forms, while dramatically outperforming traditional methods under non-normality (Saesuntia et al. 2025, Nimbale and Ghute 2021). Monte Carlo simulation studies across diverse distributional scenarios including normal, t-distributions, gamma,

lognormal, and contaminated normal distributions reveal that nonparametric charts maintain stable in-control properties regardless of the underlying distribution (Xie and Qiu 2023). This robustness translates to reliable false alarm rates and predictable statistical behavior across heterogeneous business process environments where distributional characteristics may vary across different process segments or evolve over time. The relative mean index and average extra quadratic loss provide comprehensive performance metrics that capture overall effectiveness across ranges of shift sizes, consistently favoring distribution-free approaches for non-normal business processes (Saesuntia et al. 2025, Gibbons and Chakraborti 2025).

2.4.5 Performance Evaluation of Control Charts: Sample Size, Shift Detection, and Comparative Analysis

Comprehensive performance evaluation of control charts for business process monitoring requires systematic assessment across multiple dimensions including sample size effects, shift size sensitivity, and computational efficiency. Sample size represents a critical design parameter that directly influences both detection capability and resource requirements. Larger samples provide more precise parameter estimates and greater statistical power for detecting shifts, but incur higher inspection costs and introduce temporal delays in signal generation (Nafisah et al. 2025, Ganguly and Patel 2019, Grigg and Spiegelhalter 2008). Variable sample size schemes offer an adaptive compromise, increasing sample size when process status appears questionable while using smaller samples when the process appears stable (Niaki et al. 2014, Daudin 1992).

The relationship between sample size and detection performance exhibits nuanced patterns that differ between traditional and distribution-free approaches. For traditional parametric charts under normality, increasing sample size monotonically improves shift detection through reduced sampling variance of the charting statistic (Teoh et al. 2025, Peerajit 2020). However, this improvement saturates as sample size grows large, exhibiting diminishing returns beyond certain thresholds typically around n=15-25 for most practical applications (Khilare 2025). Distribution-free charts display similar trends but often require slightly larger samples to achieve equivalent power as parametric competitors under normality, reflecting the efficiency cost of nonparametric methods (Abbas et al. 2022, Tapang et al. 2016). This efficiency gap narrows or reverses under non-normality, where distribution-free approaches maintain consistent performance while traditional charts suffer degradation (Abbas et al. 2024a, Alduais and Khan 2023).

Shift size sensitivity constitutes another crucial performance dimension, with control charts exhibiting differential effectiveness across the spectrum from small

gradual drifts to large abrupt jumps. Traditional Shewhart charts excel at detecting large shifts (1.5σ) due to their lack of memory, responding immediately to extreme observations without dilution from historical data (Raza et al. 2024, Crowder 1987). Conversely, EWMA and CUSUM charts demonstrate superior performance for small to moderate shifts (0.25σ - 1.0σ) through their cumulative tracking mechanisms that integrate information across multiple samples (Raza et al. 2024, Hawkins and Olwell 2012, Siegmund 2013). Distribution-free variants of these memory-based charts preserve this small-shift sensitivity while gaining robustness advantages (Mukherjee and Chakraborti 2012). The non-parametric TEWMAMA control chart, employing triple exponential smoothing with sign statistics, demonstrates particularly strong performance across the 0.5σ to 1.5σ shift range common in business process quality deviations (Saesuntia et al. 2025, Hu and Sun 2015).

Comparative analyses employing expected average run length metrics accommodate uncertainty about shift size by averaging ARL values across a specified range of shift sizes weighted by their relative likelihood (You et al. 2023, Lu and Reynolds Jr 2001). This approach recognizes that practitioners often cannot predict exactly what size shift may occur, necessitating designs that balance performance across multiple scenarios rather than optimizing for a single shift level. Results indicate that distribution-free approaches generally achieve superior EARL values compared to traditional charts when applied to non-normal business processes, particularly for shift intervals encompassing small to moderate sizes (Abbas et al. 2024a, Qiu and Hawkins 2001). The relative mean index, which measures average detection speed relative to a reference chart, provides another useful comparative metric that clearly demonstrates the advantages of nonparametric methods in uncertain distributional environments (Gandy and Kvaløy 2013).

2.5 Summary and contribution to literature

In this section, I summarize the most important findings of the SLR with special regard to the deficiencies of the analyzed research areas. Finally, I determine how this research contributes to the scientific literature.

Chapter 2 offered an extensive theoretical and empirical basis for the dissertation through a combined review of ESPC literature, and the possibility of its integration with Business Process Management (BPM). The SLR carried out with a PRISMA-based approach guaranteed the work's rigor, openness, and repeatability in finding and assessing studies up to 2024.

The main findings can be summarized as follows:

1. **Evolution of ESPC design types:** Research initially focused mostly on ED methods. Later, it expanded to ESD with RBD being more recent. While ED

dominated earlier decades, ESD has gained prominence due to its balanced consideration of both statistical and economic performance. RBD, although promising, remains underrepresented.

2. **Methodological Limitations in ESPC:** Over half of the reviewed studies (52.11%) identified MA and AC as primary limitations in implementing ESPC. Other challenges include PE and LA.

3. **Industrial application patterns:** ESPC applications have a major focus on manufacturing sectors such as the production of food, automotive, chemicals, and mechanical parts. On the other hand, service sectors and business process environments at large are still far to be tapped efficiently, thus confirming that the majority of the applications are manufacturing-oriented.

4. **Distributional assumptions:** It is a fact that a substantial proportion of the research in ESPC assumes normality . Besides, only a few studies resort to other distributions (Weibull, exponential, Burr, etc.). In spite of this, some studies are deeply attached to the idea of parametric assumption. The problem is that in a real-world scenario, many business processes are characterized by skewness, heavy tails, and multimodality, which hardly conform to the normal distribution.

5. **Control charts in Business process environments:** The review of BPM literature highlights the growing importance of integrating control charts with EPC modeling. Under non, normality, which is for instance very common in service and business process data, traditional parametric control charts (Shewhart, EWMA, CUSUM) will show a decrease in their actual performance.

Distribution-free and non-parametric control charts have shown robust performance across heterogeneous distributions and maintain stable in-control properties. However, their integration into structured business process modeling frameworks remains limited.

Contribution to the literature

Chapter 2 offers a thorough review of studies concerning ESPC, control chart techniques, and their prospective integration with BPM. This study enhances the literature significantly, as shown by the comprehensive literature review and analytical categorization detailed in Sections 2.1 to 2.4.

C_1 : Bridging ESPC and business process management: The literature demonstrates a clear separation between:

- ESPC studies (largely manufacturing-focused), and
- business process modeling research (largely structural and workflow-oriented).

This thesis contributes by conceptually and methodologically linking ESPC with business process management through the integration of control charts into EPC-based business process structures. This represents a shift from production-centered SPC toward process-centered organizational monitoring.

C_2 : Identification of structural gaps in ESPC research: The SLR provides a structured classification (via the proposed TCC framework) of economic models, design types, validation approaches, distributional assumptions, and industrial applications. This structured analysis exposes three major research gaps:

- excessive concentration in manufacturing sectors,
- heavy reliance on parametric assumptions (especially normality),
- Limited advances of risk-based and distribution-free methodologies within business process environments.

By systematically quantifying these gaps, the dissertation offers a clear research agenda for extending ESPC beyond its traditional boundaries.

C_3 : Addressing non-normality in business processes: The literature review demonstrates that business process data frequently violate normality assumptions. Traditional control charts, when applied without modification, lead to distorted ARL performance and unreliable detection behavior. This study contributes by:

- Emphasizing the necessity of distribution-free monitoring in business processes
- Positioning non-parametric approaches as theoretically and practically superior under realistic business data conditions
- Providing a foundation for developing a distribution-free OP control chart.

Chapter 3

Method

The literature review Chapter 2 has identified several significant gaps in the existing literature of ESPC and business process monitoring. One major finding was that ESPC implementations are still mainly limited to manufacturing settings and hardly ever combined with business process management systems. On top of that, control charts still mostly rely on strong parametric assumptions, like normality, even though business process data often show skewness, heavy tails, and heterogeneous distributions. Also, control charts that do not rely on assumptions about the distribution, while clearly more robust, have not been sufficiently applied to business processes.

This chapter outlines the techniques that were used in this dissertation to overcome these weaknesses. Our approach combines business process modeling with statistical process monitoring so that we can assess how well distribution-free control charts perform in real-life business process scenarios.

In particular:

Section 3.1 discusses how business process can be represented structurally for monitoring through the use of EPCs.

Section 3.2 describes the process control setup and outlines the way process observations are acquired and tracked.

Section 3.3 sets forth the control chart techniques engaged in the research that comprise both the conventional parametric methods and the novel distribution-free control chart structure.

Section 3.4 describes the simulation technique that is employed to measure the chart performance when subjected to different levels of non-normality, shift sizes, and sample sizes.

All these methodological ingredients combined lay down the research infrastructure to resolve Research Questions 2 (Q2) and 3 (Q3) by studying the behavior of control charts in non-normal business process scenarios.

3.1 Business process modeling

Chapter 2 shows that current ESPC research focuses mostly on manufacturing systems and offers little guidance for tracking organizational or service-based operations. To apply statistical process monitoring in such settings, a structured way to describe business workflows is needed. This study uses EPCs to represent operational sequences and spot measurable tasks that can be monitored using statistical methods.

Through its structure, the EPC system breaks down complex business processes into clear, step-by-step parts. This setup makes it possible to introduce control charts into everyday business process management practices.

3.1.1 Business and operation process modeling

This section aims at changing business activities into operational elements that are measurable and can be statistically controlled. Business process environments vary a lot from manufacturing systems not only with variability but also in the event structure. So, the modeling phase becomes something important to determine the right locations for monitoring and the indicators of process performance.

To represent business (operation) processes, EPC modeling is a technique commonly used. In EPC, the common elements are as follows:

- *Processes* encompass the complete series of events and functions that constitute an OP;
- *Functions* are activities, task, or operations performed within a business process and are depicted as rounded rectangles in the EPC diagram;
- *Events* are occurrences that indicate when a process starts, progresses, or ends, and serve as triggers for functions (tasks or activities). Events are typically represented as hexagons in EPC diagrams;
- *Logical operators* are used to control the flow of processes by defining decision points, parallel executions, and process synchronization. There are three types of logical operators: (a) the AND $(\wedge)$ *operator* splits or merges process flows so that all paths are executed simultaneously; (b) the OR $(\vee)$ *operator* splits or merges process flows, allowing one or more paths to be executed and are infrequently used; and (c) the *Exclusive OR* (XOR) *operator* indicates an exclusive decision, where only one path must be met before an event or function can be executed.

Lead time and costs are assigned only to processes in the EPC. Event only introduces or concludes the processes. In an EPC diagram, an *Exclusive* $OR(XOR)$

operator is used when a decision must be made between multiple mutually exclusive paths (thus only one of the available paths can be executed at a time). This type of decision-making often involves probabilities or relative frequencies, which determine the likelihood of each possible outcome.

The process modeled in Figure 3.1 models the processing of a client order. The process starts with the event *client order received*. First the client order data is reviewed, and as a result of this function the order is either rejected or accepted. The *XOR* connector models the fact that after the execution of the function *compare client order data* one of the two events (*client order accepted* or *client order rejected*) holds. If the order is rejected, the process stops. For each accepted order, the availability is checked. If the books are not available, then two functions are executed in parallel: *purchase material* and *make production plan*. After executing both functions, the articles are produced. If either the event *books available* or the event *finished product* holds, then the function *ship order* can be executed. After the order has been shipped, the bill is sent. After sending the bill, it is checked whether the bill has been paid (function *review payment*). If the review has a positive outcome, the process is completed (event *client order completed*). Otherwise the review is repeated until the outcome is positive. The example shown in Figure 3.1 shows that EPCs are easy to read.

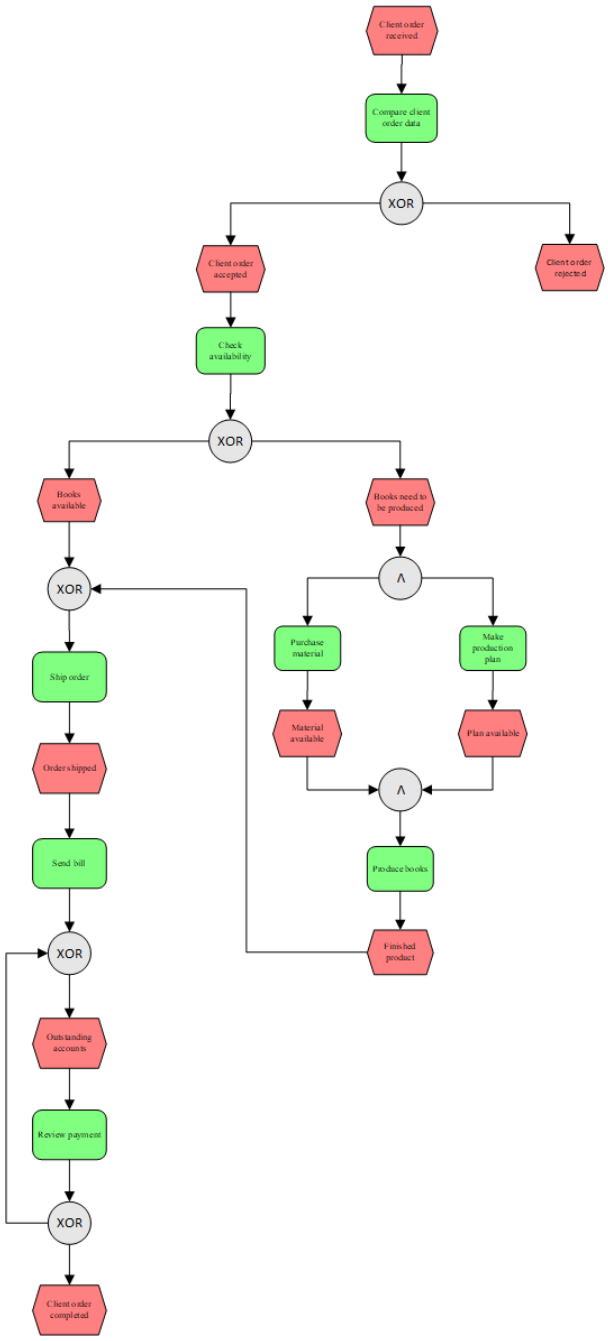


Figure 3.1: Modeling of a business process, using EPCs (Source: (Kosztyán et al. 2026))

3.1.2 Formulation of Event-drive Process Chains

Monitoring shifts from static diagrams to real-time performance tracking. The EPC formulation sets up a structured basis for this makeover by mapping events, functions, and process links. Observations are tied right to actual operations through this representation. This alignment enables continuous evaluation of process behavior over time.

Not every diagram composed of events, functions, and connectors is a correct

EPC. For instance, it is not allowed to connect two events to each other (Van der Aalst 1999). Unfortunately, a formal syntax for EPCs is missing. In this section, a formal definition of an EPC is provided. This definition is based on the restrictions described in Van der Aalst (1999) and imposed by tools such as ARIS and SAP R/3. Therefore, I specify the requirement that an EPC should satisfy.

Definition 1 *Event-driven process chain (1)*
An EPC is a five-tuple (E, F, C, T, A):

- E_k is a finite set of events, where $k = 1, 2, 3, ..., n$
- F_k is a finite set of functions, where $k = 1, 2, 3, ..., n$
- C is a finite set of logical connectors
- $T \in C \rightarrow \{\wedge, XOR, \vee\}$ is a function, which maps each connector onto a connector type
- $A \subseteq \{E_k \times F_k\} \cup \{F_k \times E_k\} \cup \{E_k \times C\} \cup \{C \times E_k\} \cup \{F_k \times C\} \cup \{C \times F_k\} \cup \{C \times C\}$ is a set of arcs

An EPC is composed of three types of nodes: events (E), functions (F) and connectors (C). the type of each connector is given by the function T : $T(c)$ is the type $(\wedge, XOR, \vee)$ of a connector $c \in C$. Relation A specifies the set of arcs connecting functions, events and connectors. Definition 1 shows that it is not allowed to have an arc connecting two functions or two events.

Definition 2 *Directed path, elementary path*
Let EPC be an event-driven process chain. A directed path p from a node n_1 to a node n_k is a sequence $\{n_1, n_2, \ldots, n_k\}$, so that $\{n_i, n_{i+1}\} \in A$ for $1 \leq i \leq k-1$. p is elementary iff for any two nodes n_i and n_j on p, $i \neq j \Longrightarrow n_i \neq n_j$.

The definition of the directed path will be used to limit the set of routing constructs that may be used. It also allows for the definition of C_{EF} (the set of connectors on a path from an event to a function) and C_{FE} (the set of connectors on a path from a function to an event). C_{EF} and C_{FE} partition the set of connectors C. Based on the function T, I also partition Cinto $C_\wedge$,$C_\vee$, and C_{XOR}. The sets C_J and C_S are used to classify the connectors into join connectors and split connectors.

Definition 3 *($N, C_\wedge, C_\vee, C_{XOR}, *, C_J, C_S, C_{EF}, C_{FE}$)*
Let EPC $= (E, F, C, T, A)$ be an *event-driven process chain*.

- $N = E \cup F \cup C$ is the set of nodes of EPC

- $C_{\vee} = \{c \in C \mid T(c) = \vee\}$
- $C_{\wedge} = \{c \in C \mid T(c) = \wedge\}$
- $C_{XOR} = \{c \in C \mid T(c) = XOR\}$
- For $n \in N : {*n} = \{m \mid (m,n) \in A\}$ is the set of input nodes, and $n{*} = \{m \mid (n,m) \in A\}$ is the set of output nodes
- $C_J = \{c \in C \| * c \| \geq 2\}$ is the set of join connectors
- $C_S = \{c \in C \| c* \| \geq 2\}$ is the set of split connectors
- $C_{EF} \subseteq C$ so that $c \in C_{EF}$ if and only if there is a path $p = \langle n_1, n_2, \ldots, n_{k-1}, n_k \rangle$, so that $n_1 \in E$, $\{n_2, \ldots, n_{k-1}\} \in C$, $n_k \in F$, and $c \in \{n_2, ..., n_{k-1}\}$
- $C_{FE} \subseteq C$ so that $c \in C_{FE}$ if and only if there is a path $p = \langle n_1, n_2, \ldots, n_{k-1}, n_k \rangle$, so that $n_1 \in F$, $\{n_2, \ldots, n_{k-1}\} \in C$, $n_k \in E$, and $c \in \{n_2, ..., n_{k-1}\}$

Consider for example the logical connector c connecting the function *check availability* and the events books available and books need to be produced in Fig. 1. Connector c and two events, i.e. $c \in C_{XOR}$, $c \in C_s$, and $c \in C_{FE}$. Definition 3 enables us to specify the additional requirements an EPC should satisfy.

Definition 4 *Event-driven process chain (2)* An EPC i.e. EPC $= (E, F, C, T, A)$ satisfies the following requirements:

- The sets E, F, and C are pairwise disjoint, i.e. $E \cap F = \varnothing$, $E \cap C = \varnothing$, and $F \cap C = \varnothing$.
- For each $e \in E : | *e | \leq 1$ and $| e* | \leq 1$
- There is at least one event $e \in E$, so that $| *e | = 0$ (i.e. a start event)
- There is at least one event $e \in E$, so that $| e* | = 0$ (i.e. a final event)
- For each $f \in F : | *f | = 1$ and $| f* | = 1$
- For each $c \in C : | *c | \geq 1$ and $| c* | \geq 1$
- The graph induced by EPC is weakly connected, i.e. for every two nodes n_1, $n_2 \in N$, $(n_1, n_2) \in (A \cup A^{-1})^*$
- C_J and C_S partition C, i.e. $C_J \cap C_S = \varnothing$ and $C_J \cup C_S = C$
- C_{EF} and C_{FE} partition C, i.e. $C_{EF} \cap C_{FE} = \varnothing$ and $C_{EF} \cup C_{FE} = C$

3.2 Process control

Chapter 2 showed traditional statistical process control methods lose effectiveness on non-normal business process data. Nevertheless, process monitoring remains essential for detecting operational shifts and maintaining process stability.

The control system introduced here outlines the monitoring logic, sampling approach, and performance indicators used to assess operational behavior. It is tailored for business processes where variability does not conform to standard parametric expectations.

This section reviews the performance of different control charts on OPs. The analyzed control charts are the (1) traditional Shewhart X-bar chart, (2) X-bar chart with permutation-computed control lines, (3) Median chart and (4) Standardized Mean–Rank (SMR) chart.

X-bar chart The traditional Shewhart X-bar chart uses the sample means as the chart statistic. Let the number of samples be m; each sample has a size of n, and X_{ij} denotes the j^{th} observation for the i^{th} sample (where $i = 1, ..., m$ and $j = 1, ..., n$). The traditional X-bar chart assumes that X_{ij} follows a normal distribution with the expected value μ and standard deviation σ ($X_{ij} \sim N(\mu, \sigma)$). The upper and lower control limits (UCL and LCL, respectively) are calculated as follows (Goedhart et al. 2017):

$$UCL = \mu + k_\alpha \frac{\sigma}{\sqrt{n}} \tag{3.1}$$

$$LCL = \mu - k_\alpha \frac{\sigma}{\sqrt{n}} \tag{3.2}$$

where α is the False Alarm Probability (FAP), k is the control limit coefficient of the corresponding selected α value, and $k_\alpha = \phi^{-1}(1 - \alpha/2)$ and $\phi^{-1}(x)$ are the inverses of the standard normal cumulative distribution function.

Distribution-free X-bar chart The distribution-free version of the X-bar chart (denoted the DF X-bar below) follows the same logic as the control chart does. The only difference is in the calculation of the control limits. While the traditional X-bar chart sets the control limits by selecting an α value and calculates k analytically afterward, the DF X-bar chart uses permutation to calculate the control lines. To obtain the control lines for the desired FAP, the permutations comprise the following steps:

1. Calculation of the selected control chart statistics from the observations,

2. permutation of the samples from the initial chart statistics without replacement and

3. determination of the control lines by averaging the $100(1-\alpha)$ percentile values (Ikpotokin and Ishiekwene 2016).

   During the permutation, Monte Carlo simulation is performed; the goal is to find the optimal value for k to achieve a desirable value of FAP. The resulting control limits are distribution free (Capizzi and Masarotto 2018).

Median chart For the median chart, the sample median can be calculated as follows (Castagliola and Figueiredo 2013):

$$\tilde{X}_i = \begin{cases} X_{i,(n+1)/2}, & \text{if } n \text{ is even} \\ \frac{X_{i,(n/2)}+X_{i,(n/2+1)}}{2}, & \text{if } n \text{ is odd} \end{cases} \tag{3.3}$$

where $\tilde{X}_i$ is the sample median for the i^{th} sample. The control lines are calculated as follows:

$$UCL = \mu + k\sigma \tag{3.4}$$

$$LCL = \mu - k\sigma \tag{3.5}$$

Although initially, the control limits for the median chart are calculated with the formula defined above, in this study, a permutation-based approach is used for the median chart calculated in the R program via the "dfphase1" package (Capizzi and Masarotto 2018).

Standardized mean rank chart The Standardized Mean–Rank chart (SMR chart in the following) assigns $R_{ij} = 1, 2, ..., N$ integer values to the X_{ij} observations on the basis of their ranks in the population, where the pooled sample size is N and $N = m \times n$ (in the case of ties, the midrank method is applied). The mean and variance of the rank values can be described as follows (Jones-Farmer et al. 2009):

$$\overline{R_{ij}} = \frac{N+1}{2} \tag{3.6}$$

$$var(R_{ij}) = \frac{(N-1)(N+1)}{12} \tag{3.7}$$

If they are calculated for samples, the mean and variance can be expressed as follows:

$$E(\overline{R_i}) = \frac{N+1}{2} \tag{3.8}$$

$$var(\overline{R_i}) = \frac{(N-n)(N+1)}{12n} \tag{3.9}$$

After standardization, the random variable

$$Z_i = \frac{\overline{R_i} - E(\overline{R_i})}{\sqrt{var(\overline{R_i})}} \tag{3.10}$$

follows a standard normal distribution on the basis of the central limit theorem if n is sufficiently large. For the SMR chart, the centerline is zero (CL=0), and UCL and LCL are estimated via simulation, where the goal of the optimization is to achieve the desired FAP value.

3.3 Control charts for business processes

From the review of literature, two significant issues related to business process monitoring emerged. One, conventional control charts like Shewhart, EWMA, and CUSUM are heavily dependent on the assumption of normality. Secondly, although distribution-free methods have shown top-notch robustness to non-normal situations, their application in business process scenarios is still under-researched.

Making use of these points as a basis, this study compares a set of conventional parametric control charts as well as a new distribution-free control chart in an EPC-based business process model.

The purpose is twofold:

1. To evaluate the performance of traditional control charts under non-normal business process conditions (addressing Q2).

2. To determine if the new distribution-free control chart can detect shifts more reliably under different process conditions (addressing Q3).

In this study, I apply phase I charts and assume that the observed and control values are independent and identically distributed. Figure 3.2 illustrates the logic behind the monitoring and control of an OP with a control chart.

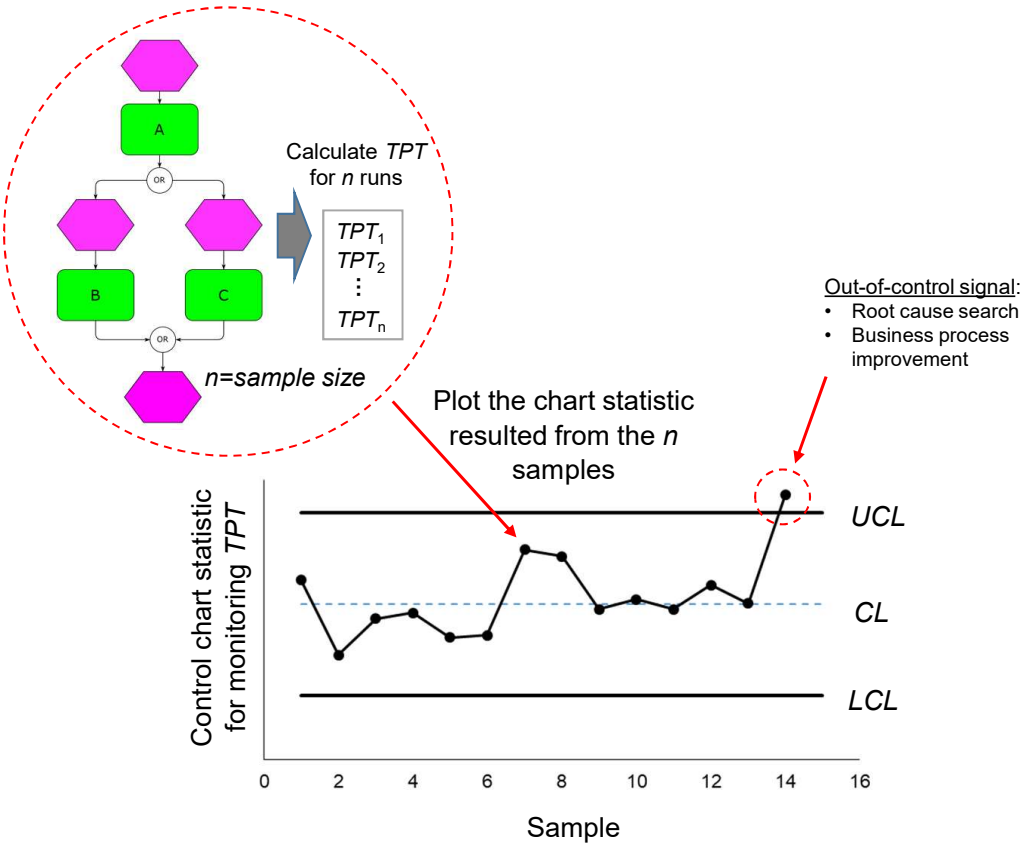


Figure 3.2: Schematic figure of an operation process control chart

The OPs, which are tracked and controlled, reoccur multiple times in a year, month or week. These OPs can have different subjects or clients or be performed with the same actors and items but have different decisions within the workflow modeled by the same EPC; thus, different routes of the EPC are activated. These routes can result in different throughput times, resource usages or operational costs. The aim of the OP chart is to monitor these repetitive processes, described with the same EPC, to distinguish what variances in the process measures are natural and what the products of systematic deviations and assignable causes are. The identification of assignable causes is the basis of process improvement through the elimination of causes of negative deviations or the exploitation of sources of positive deviations (e.g., by making good practices on the basis of these positive deviations). As Figure 3.2 shows, each data point on the OP chart is obtained via observations and measurements of multiple instances of the same OP. In other words, an OP is specified and modeled with EPC, and characteristics such as TPT and Total Process Cost (TPC) can be calculated after each complete run of the entire OP. The TPT or TPC values for each run can be structured into samples, and the control chart statistic can be calculated from the sample comprising n observations (see Figure 3.2). If an out-of-control signal is detected, the chart indicates that the expected duration or the expected total cost of the OP has changed. In that case, a root-cause search must be performed to detect the assignable causes, and the process must be improved by eliminating the blocking factors. Note that TPT and TPC can be monitored; however, in Figure 3.2, TPT is monitored as an illustration for simplicity. To monitor the operation process, the OP chart type must be selected, and the control chart parameters must be designed. When analyzing OP data, it is important to consider that there may be cases where only one control limit is applicable. This statement is particularly true when the lower control limit falls below zero or when logically impossible conditions exist. The proposed chart fitting procedure is shown in Figure 3.3.

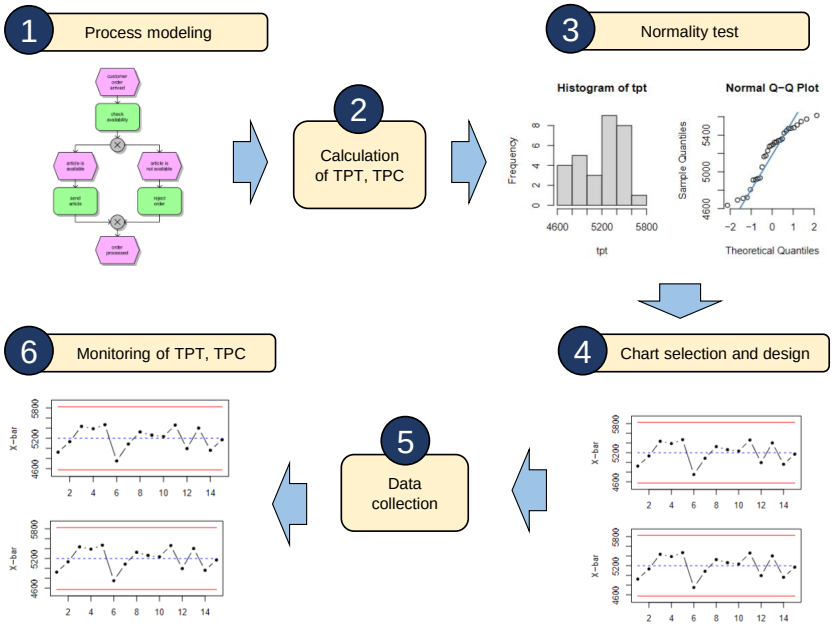


Figure 3.3: Steps for fitting control charts

As shown in Figure 3.3, the proposed OP control chart design and application comprises six steps: (1) process modeling, (2) calculation of TPT and TPC, (3) normality testing, (4) control chart selection and design, (5) continuous data collection and (6) monitoring of the OP. In the following, I discuss these steps in detail.

1. **Process modeling**

   First, the selected OP needs to be modeled through the determination of each process, subprocess, and event of the selected OP. In addition to the processes and events, all the logical operators, such as *AND*, *OR*, and *XOR*, must be specified to ensure that all possible parallel runs and decisions are identified in OP. In this step, the EPC diagram can be used for OP modeling.

2. **Calculation of *TPT* and *TPC***

   Using the structure of OP specified in step (1), the TPT and TPC of the process are calculated as described in subsection 3.1. At this step, the data must be observed multiple times, and TPT and TPC must be calculated for each run. These necessities emerge because, in the following steps, the first TPT and TPC series constitute the basis for calculations such as normality tests and control chart phase 1 analysis. At this step, I recommend performing at least 30 observations for running the selected OP. This action generates at least 30 TPT and TPC values, which is the minimum required number of data points for several normality tests.

3. **Normality test**

An OP comprises several tasks (processes), each of which can follow a certain type of distribution in terms of cost or duration; thus, it cannot be guaranteed that the aggregated OP's TPT and TPC are normally distributed. Normality testing is important since it determines whether a traditional Shewhart chart can be used, such as an X-bar chart, or whether selecting and designing a distribution-free control chart is necessary. To conduct the normality test, I suggest using the Shapiro–Wilk test because it has good power properties and is a widely used method for testing normality (Das and Imon 2016). The Shapiro–Wilk test is based on the correlation between the observed data values and the corresponding normal scores. The test statistic can be formulated as follows:

$$W = \frac{(\sum a_i y_i)^2}{\sum (y - \overline{y})^2} \tag{3.11}$$

where y_i is the ith observed order statistic and a_i is the corresponding expected normalized order statistic. In the case of normality, the value of W is close to 1; during hypothesis testing, normality is rejected if W is significantly less than 1. The Shapiro–Wilk test was developed for testing normality; however, it is important to test whether a sample follows a specified theoretical distribution outside the normal distribution. For this purpose, the Kolmogorov–Smirnov test is widely used. The test statistic, denoted as D, can be defined as follows (Das and Imon 2016):

$$D = sup_x |F_n(X) - F(X)^*| \tag{3.12}$$

where $F_n(X)$ denotes the empirical distribution function of the sample and $F(X)^*$ is the assumed theoretical distribution function. A large value of D indicates that the sample follows a different distribution than the theoretical distribution. The Kolmogorov–Smirnov test applies to continuous cases. In the case of a discrete task duration distribution, the chi-square test can be used to test the distribution type. The test statistic is calculated as follows:

$$\chi^2 = \sum_{i=1}^{r} \frac{(n_i - n_i^*)^2}{n_i^*} \tag{3.13}$$

where r is the number of categories and n_i^* is the expected number of elements (based on a theoretical distribution) in category i, where n_i is the observed number of elements.

In addition to statistical tests, normality can be tested visually. The Q–Q (quantile–quantile) plot is an excellent tool for visually examining the dif-

ferences between theoretical and observed distributions. The Q–Q plot is a straight line representing the best fitting case, which is when the theoretical and observed quantiles are equal.

4. **Control chart selection and design**

   In this step, the proper control chart is selected to control OP. If step (3) confirms a normal distribution, the Shewhart X-bar chart can be used since the assumptions are fulfilled, and this chart is also a good choice because of its simplicity. Otherwise, a distribution-free control chart needs to be selected. To select the best-performing distribution-free control chart, the in-control average run length (ARL_0) and out-of-control average run length (ARL_1) values can be considered. Control chart performance is affected by various factors, such as the size of the expected process shift or sample size. The ARL values can be estimated through simulations. In this study, I provide recommendations for selecting the best-performing control chart to control the OP sample size and expected shift size. To obtain the rules for selecting the best performing control chart considering different process parameters, such as sample size or process shift size, the decision tree algorithm is used. Decision trees are used in computer science to reveal the influencing features and extract patterns in large datasets. Decision trees recursively partition the feature space to find a set of decision rules that provide an informative and robust hierarchical classification scheme (Myles et al. 2004).

5. **Continuous data collection**

   After the control chart is selected and designed, i.e., the sample size is chosen, the control limits are calculated, and phase 1 analysis ends. To monitor and, if necessary, control the OP, continuous data collection related to the TPT and TPC values is needed. In this step, the integration of an enterprise resource planning (ERP) system can automate the calculation of the entire OP duration and cost every time OP ends. The calculation of the TPT or TPC values is not computationally intensive, and for most OPs, requires several orders of magnitude less time than the lead time or frequency of occurrence of OP. Data collection could be a challenge, especially for workflows and activities that are not logged directly in an Enterprise Resource Planning (ERP) or other information system. These data are subject to measurement uncertainty, perturbation, noise, or delay in registration.

6. **Monitoring of TPT and TPC**

   If the data are collected continuously, each new TPT and/or TPC value can be plotted on its corresponding OP chart. In an out-of-control situation, the

assignable cause of the shift must be investigated, and correctional intervention should be performed.

3.4 Simulation process

To evaluate the performance of each control chart, simulations are conducted to obtain the ARL_0 and ARL_1 values. The steps of the simulations are described below.

ARL_0 evaluation:

1. Perform distribution identification for each task in OP.
2. Generate the TPT series via Monte Carlo simulation.
3. Fit the control chart to the simulated TPT.
4. For each control chart, determine the location of the first point indicating a (false) out-of-control signal (run length).
5. Iterate steps 2–4 and save the run length values for each control chart from each iteration.
6. Calculate the average (median and standard deviation) of the run length values to obtain ARL_0 (MRL_0 and $SDRL_0$) for each control chart.

For a given OP (real-life example), the *PearsonDS* R package is used to estimate the four moments of the distribution: the mean, standard deviation, skewness and kurtosis. After the four moments of the distribution for each task are obtained, random duration values are generated with the estimated distribution (using the four estimated moments). The simulated TPT is calculated in each iteration as the aggregation of the generated durations, as discussed in subsection 3.1. Each analyzed control chart is fitted to the simulated TPT series with a given sample size. The ARL_0 value is calculated for each control chart as described in steps 4–5. This simulation is conducted for different sample sizes for each control chart.

ARL_1 evaluation:

1. Perform distribution identification for each task in OP.
2. Generate the TPT series via Monte Carlo simulation.
3. Simulate a shift in the series with a selected shift size, starting at a given location.
4. Calculate the limits for each control chart considering the first m chart statistics before the shift occurs.
5. Calculate the length from the shift starting point to the first out-of-control signal (run length).

6. Iterate steps 2–5 and save the run length values for each control chart from each iteration.

7. Calculate the average (median and standard deviation) of the run length values to obtain ARL_1 (MRL_1 and $SDRL_1$) for each control chart.

The structure of the simulation is similar to that of the simulation related to ARL_0 estimation. The most important difference is shift generation. The shifted TPT series is described as follows:

$$TPT_s(i) = \begin{cases} TPT_g(i), & \text{for i} < l \\ TPT_g(i) + z\sigma, & \text{for i} \geq l \end{cases} \tag{3.14}$$

where $TPT_g(i)$ is the i^{th} value of the generated TPT series, $TPT_s(i)$ is the i^{th} value of the shifted TPT series, σ is the standard deviation of the controlled process, l is an integer representing the location of the shift as the l^{th} value of TPT_g, and z is a coefficient representing the shift size in terms of standard deviation. An example of a generated process shift is shown in Figure 3.4.

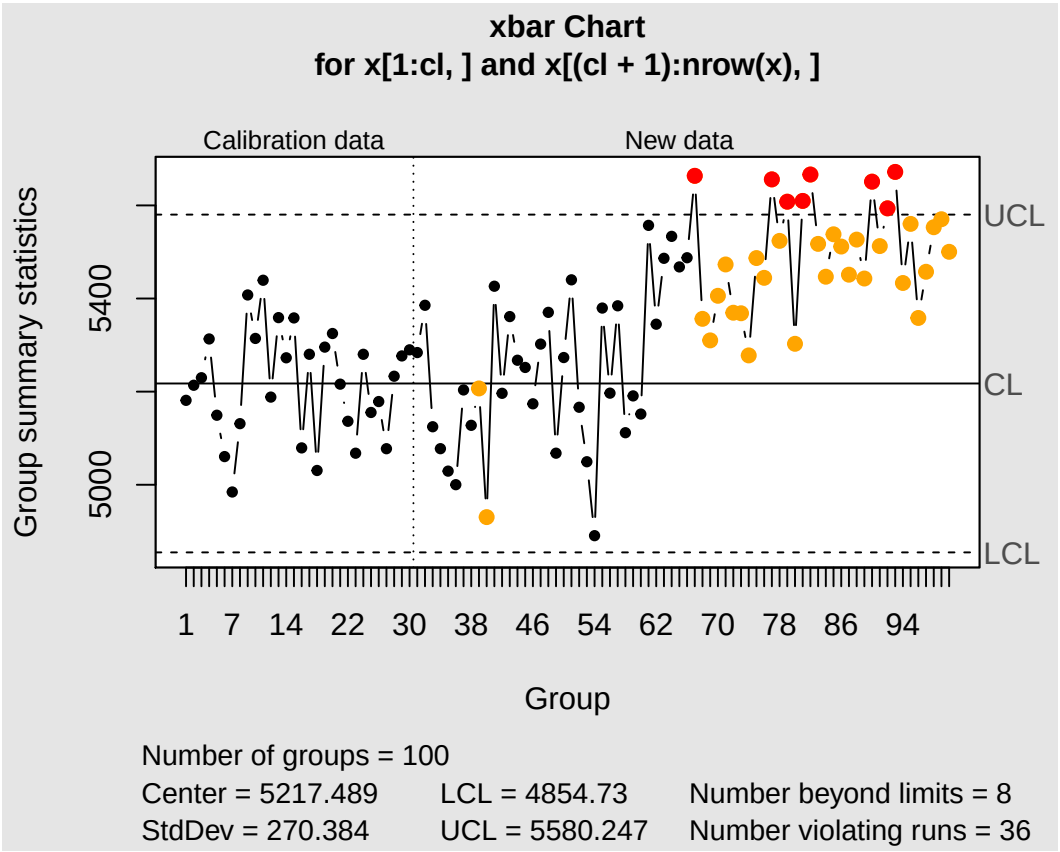


Figure 3.4: Example of a simulated process shift (Source: (Kosztyán et al. 2026))

An X-bar chart is shown in Figure 3.4, where the first 30 samples are used to calibrate the chart, i.e., calculate the centerline and the control limits. A $z = 1.5$

shift occurs after the 60^{th} sample, and the chart detects the shift at the 67^{th} sample; therefore, the run length is 7 in this case. This iteration is repeated several times, and the ARL_1 value is estimated as the average of the run length values given by each iteration. The simulation is conducted with different sample sizes (n) and different shift sizes (z).

Chapter 4

Case Study

This chapter presents a case study of a machine repair process comprising 36 tasks, which demonstrate control chart usage in an operational environment, and to investigate control chart performance. I selected this process as a case because it involves diverse types of operational tasks, including reparation, planning, and invoice creation. In this way, I can use and analyze various control charts in an adequately complex environment.

The structure of OP is shown in Fig. 4.1.

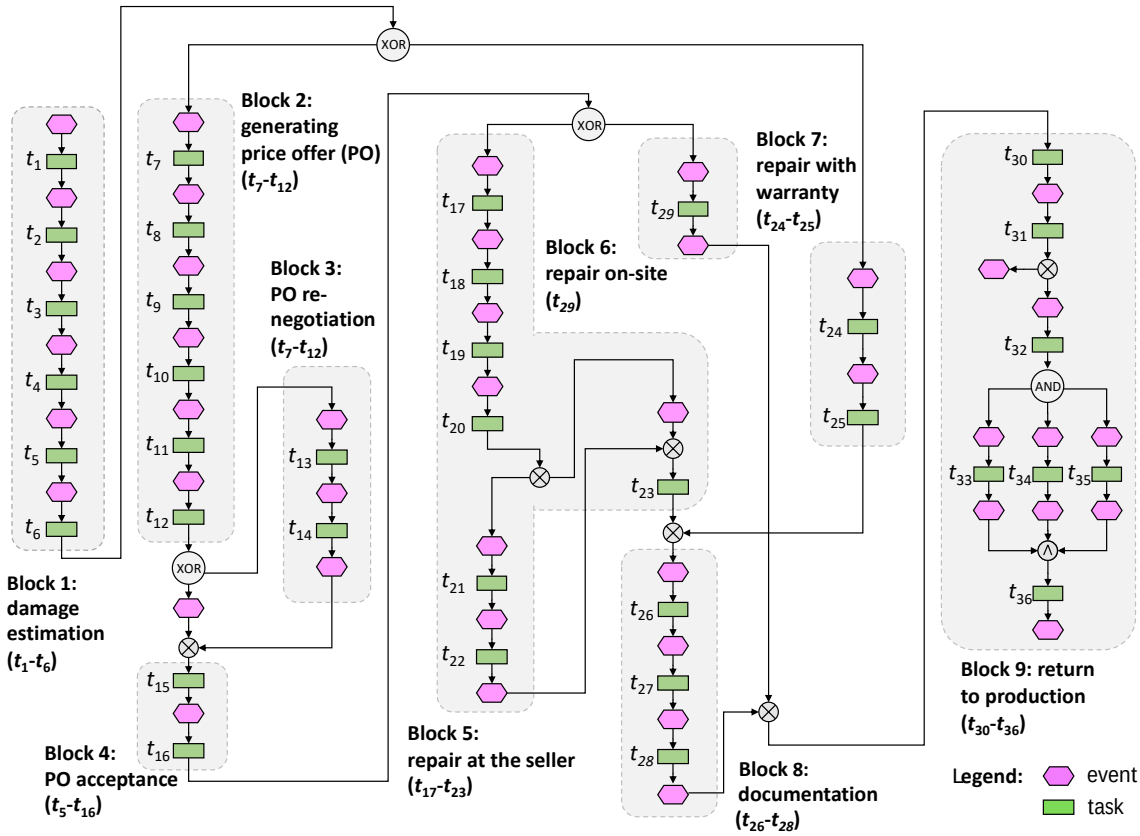


Figure 4.1: Process flow diagram of the machine repair process. The gray blocks represent the main task groups.

The machine repair process for production equipment comprises 9 larger blocks. In the first block, the damage is assessed, including the failed components, parts and failure modes; then, the process is divided depending on whether the given machine has a warranty. In the case of a warranty, repair begins (Block 7); this repair can be performed on site (Block 6) or at the site of the operator's maintenance partner (Block 5). If the given machine has no warranty, a price offer will be made (Blocks 2, 3, and 4), after which the repair can be performed at the site of the company or the operator's maintenance service partner. After a successful repair, documentation is performed (Block 8), and then the equipment is restarted (Block 9).

Each task duration is independent of the previous task duration, and each duration has its own distribution, where normality cannot be guaranteed. Table 4.1 provides descriptive statistics for each task of the process, where the values represent the duration in minutes.

Table 4.1: Descriptive statistics for each task in the dataset

Task	Min.	Max.	Mean	St. Dev.
t_1	0.50	3.60	1.90	0.93
t_2	8.00	15.00	11.43	2.18
t_3	90.00	119.00	103.70	8.05
t_4	30.00	35.10	32.44	1.54
t_5	30.00	34.50	32.06	1.32
t_6	54.98	72.60	66.06	4.43
t_7	27.30	37.60	31.89	2.45
t_8	20.50	25.30	22.20	1.58
t_9	1635.00	2860.00	2355.13	398.61
t_{10}	61.00	119.00	88.10	16.50
t_{11}	30.00	35.10	32.44	1.54
t_{12}	30.00	34.70	32.60	1.43
t_{13}	61.50	113.70	85.51	16.00
t_{14}	4.90	6.30	5.60	0.50
t_{15}	30.10	34.80	32.19	1.32
t_{16}	68.30	196.00	123.83	34.70
t_{17}	60.50	116.10	88.69	16.96
t_{18}	91.40	119.10	105.93	8.40
t_{19}	30.20	34.60	32.31	1.46
t_{20}	30.30	45.00	37.67	4.20
t_{21}	60.10	72.90	67.23	3.51
t_{22}	30.20	34.90	33.04	1.41
t_{23}	108.30	119.70	113.19	5.50
t_{24}	4003.00	4121.00	4034.63	42.66
t_{25}	4003.00	4126.00	4039.47	44.16
t_{26}	30.00	35.10	32.44	1.54
t_{27}	30.00	35.10	32.44	1.54
t_{28}	30.00	35.10	32.44	1.54
t_{29}	166.50	180.50	174.77	4.38
t_{30}	203.60	238.50	228.04	16.24
t_{31}	59.90	75.60	69.10	5.17
t_{32}	4.90	6.30	5.57	0.56
t_{33}	4.90	6.30	5.69	0.48
t_{34}	20.50	25.80	21.75	1.33
t_{35}	8.00	15.30	11.51	2.01
t_{36}	0.50	3.60	1.86	0.94

As Table 4.1 shows, tasks t_9, t_{24}, and t_{25} have significantly higher mean values than the overall average. This finding indicates that these tasks should be considered carefully because their delay can significantly affect the overall TPT. To observe the differences in the task variances, Figure 4.2 is presented, where the x-axis represents the task number and the y-axis represents the standardized values for each task. The color of each box is set on the basis of the group median.

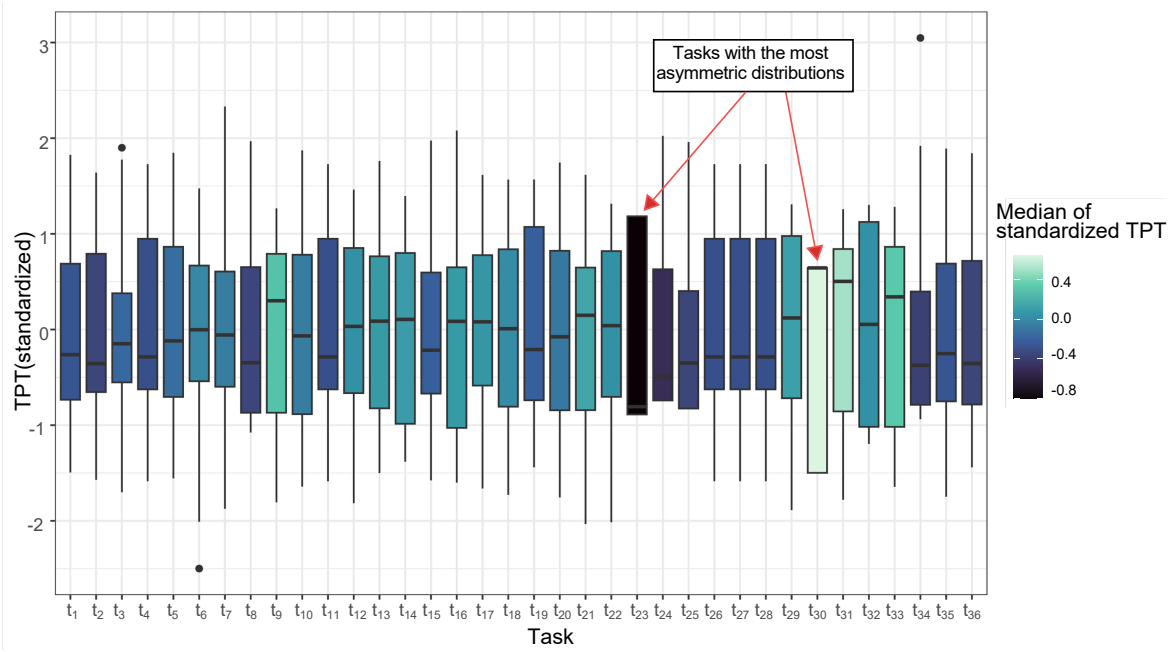


Figure 4.2: Dispersion of standardized TPT values per task. The color of the boxes represents the median of the standardized task durations, the vertical lines represent the range of durations per task, and the black dots denote outliers.

As Figure 4.2 shows, there are several strongly skewed distributions, such as those for tasks t_{23} and t_{30}. Extreme values can be observed only for tasks t_3, t_6 and t_{34}. The data in Figure 4.2 also suggest that several tasks are skewed; thus, normality cannot be fulfilled in these cases, and therefore, the overall TPT values are highly unlikely to follow a normal distribution. TPT is calculated as the aggregation of the task durations, as described in Section **??**:

$$\begin{aligned} TPT = &\sum_{1}^{6} t_i + 0.7 * \sum_{7}^{12} t_i + 0.7 * 0.2 \sum_{13}^{14} t_i + 0.7 * \sum_{15}^{16} t_i + 0.7 * 0.7 \sum_{17}^{20} t_i \\ &+ 0.7 * 0.7 * 0.1 * \sum_{21}^{22} t_i + 0.7 * 0.7 * t_{23} + 0.3 * \sum_{24}^{25} t_i + 0.3 \\ &+ 0.7 * 0.7 * \sum_{26}^{28} t_i + 0.7 * 0.3 * t_{29} + 1 * 0.1 * \sum_{30}^{31} t_i + 1 * 0.9 * \sum_{32}^{36} t_i \end{aligned} \tag{4.1}$$

where the multiplicators are derived from the probabilities of execution related to the specific operator. The execution probabilities were estimated by experts at the company, considering historical data. From a historical dataset, 30 runs of the machine repair process were collected, and TPT was calculated for each run via Eq. 4.1. The average TPT related to the collected data was 5199 [min].

At the company, the data collection and registration of the duration values are

supported by the company's integrated information system. After 30 data points (TPT values) were collected, the taskwise durations were exported to an Excel spreadsheet for each run. After data collection and analysis, the proposed OP chart was fitted to the machine repair process. Control chart usage in an operation process such as machine repair is highly valuable since without this information, the monitoring and control of the process and the identification of weak or risky tasks are difficult or even impossible.

Chapter 5

Results and Discussion

This chapter presents the empirical validation and performance evaluation of the proposed business process monitoring framework introduced in Chapter 3. The objective of the analysis is to evaluate the effectiveness of traditional and distribution-free control charts under realistic operational process conditions characterized by non-normal process behavior.

The chapter directly addresses Research Questions 2 (Q2) and 3 (Q3) through:

- simulation-based evaluation of control chart performance,
- comparison of parametric and nonparametric monitoring methods,
- fitting control charts to real operational process data, and
- sensitivity analysis under varying distributional characteristics.

When data from operational processes are analyzed, standard parametric conditions are checked first. And then, control chart performance is assessed using average run length metrics across several simulated in-control and out-of-control situations. These evaluations include both stable and abnormal process states under varying conditions.

5.1 Simulation results

Simulations employing the methodology from Chapter 3 were utilized to examine shift extents, sample sizes, and distributional conditions. These variables affected the detection of changes using traditional parametric and distribution-free control charts. The experiments assessed monitoring performance under regulated process conditions. The objective was to address Research Question 3 (Q3). The study evaluated whether distribution-free control charts surpass parametric control charts in non-normal business processes.

5.1.1 Distribution fitting and validation

To analyze the performance of the proposed control charts on the OP, a simulation is used. As the first step of the analysis, the distributions of the 38 tasks must be identified. Therefore, the four moments of each distribution are estimated. The *PearsonDS* R package was applied for the estimation. To test the goodness of fit of the simulated and real data series, the distributions are compared. The densities of the duration values related to the real and simulated data series are shown in Figure 5.1.

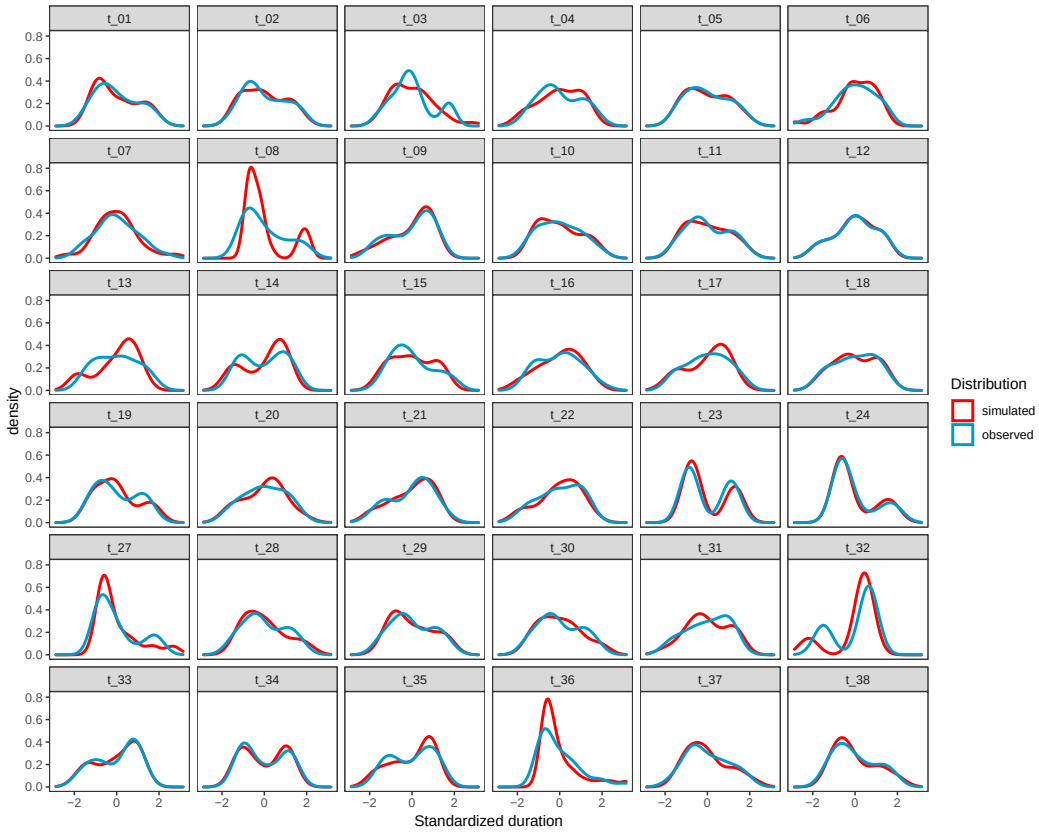


Figure 5.1: Density plot of real vs. simulated durations

As shown in Figure 5.1, the distribution moments are adequately estimated, and the resulting simulated series are close enough to the real situation to model the selected OP. As shown in Figure 5.1, the distributions of the durations related to certain tasks clearly follow various distribution types, such as centered distributions, strongly skewed distributions and distributions with multiple peaks, resulting in the aggregated TPT values following a mixed distribution. To investigate whether the simulated distributions are comparable to the real distributions, statistical tests were used, and the results are summarized in Table 5.1.

Table 5.1: Results of the nonparametric statistical tests

Kolmogorov–Smirnov test					
Tasks 1 -19			Tasks 1 - 38		
Task	D	p-value	Task	D	p-value
t_1	0.100	0.999	t_{20}	0.133	0.952
t_2	0.167	0.799	t_{21}	0.133	0.952
t_3	0.200	0.586	t_{22}	0.133	0.952
t_4	0.167	0.799	t_{27}	0.333	0.071
t_5	0.100	0.998	t_{28}	0.100	0.998
t_6	0.133	0.958	t_{29}	0.100	0.998
t_7	0.100	0.998	t_{30}	0.200	0.586
t_8	0.100	0.998	t_{31}	0.133	0.952
t_9	0.133	0.958	t_{33}	0.133	0.952
t_{10}	0.133	0.952	t_{34}	0.300	0.134
t_{11}	0.200	0.586	t_{35}	0.167	0.799
t_{12}	0.167	0.799	t_{36}	0.167	0.799
t_{13}	0.133	0.958	t_{37}	0.133	0.952
t_{14}	0.133	0.952	t_{38}	0.133	0.952
t_{15}	0.167	0.799	**Chi-square test**		
t_{16}	0.167	0.808	**Task**	χ^2	**p-value**
t_{17}	0.067	1.000	t_{23}	107.859	0.980
t_{18}	0.133	0.952	t_{24}	510.000	0.417
t_{19}	0.167	0.799	t_{32}	1.236	0.744

During the goodness-of-fit tests, three tasks are found (t_{23}, t_{24}, and t_{32}), for which the data show discrete patterns, and the Kolmogorov–Smirnov test cannot be performed because of the ties in the data values. For these cases, I run chi-square tests to examine whether the simulated and real distributions are the same. As Table 5.1 shows, the p-values are greater than 0.05 for all the tasks; therefore, the statistical tests also confirm that the simulated series are good estimates of the real data.

The validated simulation framework therefore provides a reliable basis for evaluating control chart performance under realistic business process conditions.

5.1.2 In-Control Performance Analysis

After the goodness of fit is checked, the control charts are designed, and the ARL_0 values are estimated. Table 5.2 shows the parameters of the simulation.

Table 5.2: Simulation parameters for ARL_0 performance

Parameter	**Value**
Iteration by control chart	1000
Sample sizes (n)	$[2, 3, 4, 5, 6, 7, 8, 9, 10]$
Samples to estimate control limits	30
Length of simulated TPT series	1000
Nominal ARL_0	$\sim$370
False alarm rate (α)	0.0027

Table 5.3 shows the control chart parameters calculated during the simulation for each control chart. The control limits are mean values indicating the average value calculated from one thousand iterations.

Table 5.3: Control chart parameters during the simulation

	X-bar			**SMR**		
n	$\overline{CL}$	$\overline{LCL}$	$\overline{UCL}$	$\overline{CL}$	$\overline{LCL}$	$\overline{UCL}$
2	5199.84	4623.11	5776.58	0.00	-2.35	2.35
3	5195.65	4714.39	5676.92	0.00	-2.66	2.66
4	5197.61	4788.55	5606.66	0.00	-2.81	2.81
5	5199.21	4835.22	5563.20	0.00	-2.89	2.89
6	5196.03	4872.69	5519.36	0.00	-2.94	2.94
7	5200.57	4906.75	5494.39	0.00	-2.97	2.97
8	5193.70	4921.44	5465.96	0.00	-2.99	2.99
9	5199.00	4946.40	5451.60	0.00	-3.01	3.01
10	5200.57	4965.60	5435.53	0.00	-3.02	3.02
	DF X-bar			**Median**		
n	$\overline{CL}$	$\overline{LCL}$	$\overline{UCL}$	$\overline{CL}$	$\overline{LCL}$	$\overline{UCL}$
2	5199.84	4600.67	5799.01	5211.25	4469.63	5952.88
3	5195.65	4695.06	5696.25	5204.78	4655.39	5754.18
4	5197.61	4766.43	5628.79	5206.35	4748.92	5663.79
5	5199.21	4812.06	5586.36	5205.28	4802.83	5607.72
6	5196.03	4849.76	5542.30	5200.91	4840.36	5561.47
7	5200.57	4879.63	5521.51	5203.47	4866.69	5540.24
8	5193.70	4892.17	5495.23	5197.53	4885.11	5509.95
9	5199.00	4915.72	5482.28	5200.49	4905.97	5495.01
10	5200.57	4932.81	5468.32	5204.14	4926.52	5481.75

After the durations and the TPT series are simulated, ARL_0 is estimated for each chart with different sample sizes. The simulation results are shown in Figure 5.2. Figure 5.2A shows the expected ARL_0 value for each control chart considering different sample sizes, and Figure 5.2B illustrates the dispersion of the ARL_0 values with box plots.

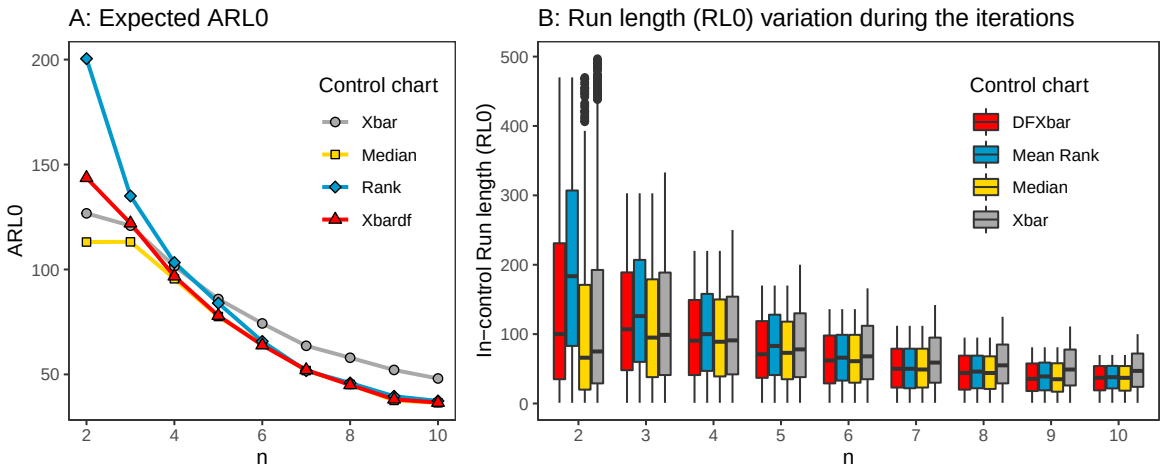


Figure 5.2: In-control ARL based on the simulation

As shown in Figure 5.2A, the distribution-free control charts outperform the conventional X-bar chart when the sample size is smaller than 5. The best solution is the SMR chart for a small sample size when $n = 2$, which achieves an ARL_0 value that is almost twice as large as that of the X-bar chart. Figure 5.2B also shows that after $n = 5$, the boxes for the distribution-free control charts overlap the interval related to the traditional X-bar chart. This finding can be explained by the effect of the central limit theorem. Specifically, the distributions of the samples with larger sample sizes ($n > 5$ in this case) tend toward a normal distribution, which equalizes the performances of the parametric and nonparametric control charts. To confirm this observation, the distributions of the control chart statistics for different sample sizes were analyzed with the Shapiro–Wilk normality test. Table 5.4 shows the results of this analysis.

Table 5.4: Results of the normality tests for different sample sizes

n	W	p	$p > 0.05$
2	0.974	0.000	
3	0.986	0.005	
4	0.982	0.007	
5	0.986	0.080	*
6	0.981	0.059	*
7	0.988	0.452	*
8	0.989	0.585	*
9	0.978	0.182	*
10	0.980	0.331	*

As Table 5.4 shows, the normality test indicates that the samples follow a normal distribution if $n \geq 5$, which confirms the effect of the central limit theorem in this

case.

The in-control performance analysis therefore directly supports Research Question 2 (Q2) by demonstrating that non-normality significantly affects control chart behavior in operational process environments, particularly when small sample sizes are used.

The ARL_0 and the in-control median and standard deviation run length values (MRL_0 and $SDRL_0$) are estimated, as shown in Table 5.5. The MRL_0 and $SDRL_0$ values are calculated for different sample sizes. The last two columns show the best performance on the basis of the maximum MRL_0.

Table 5.5: Control chart in-control performances

	Median		Mean- Rank		X-bar		DF X-bar		Best
n	MRL_0	$SDRL_0$	MRL_0	$SDRL_0$	MRL_0	$SDRL_0$	MRL_0	$SDRL_0$	MRL_0
2	117.00	129.09	139.00	113.77	68.00	105.84	87.00	99.15	SMR
3	119.00	77.49	139.50	80.62	82.50	83.95	117.00	78.73	SMR
4	78.00	69.20	80.00	71.72	64.00	60.99	80.00	63.42	SMR
5	87.50	56.84	80.00	43.50	86.50	55.40	80.00	47.38	Median
6	46.00	47.04	36.00	43.33	66.50	45.02	44.00	45.31	Xbar
7	69.00	36.21	45.00	33.92	61.00	39.46	56.00	34.71	Median
8	30.00	21.56	53.00	27.71	50.00	33.43	29.50	21.87	SMR
9	58.00	23.86	51.00	18.30	58.00	30.64	49.00	23.18	Median
10	18.00	16.73	18.00	21.50	43.50	28.64	24.00	19.47	Xbar

Note: nominal ARL_0 is set to $\sim$370 ($\alpha = 0.0027$ resulting $k = 3$)

As Table 5.5 shows, the findings are confirmed by the MRL_0 values, indicating that the SMR chart has the best performance with low sample sizes, but the X-bar chart can also be used as n increases. In contrast, the median chart is a considerable choice when stability is important in the decision ($SDRL_0$).

5.1.3 Out-of-Control Performance Analysis

To measure the performance in detecting out-of-control signals, the out-of-control ARL values (denoted ARL_1) were computed during an additional simulation. In this simulation, 30 samples were used to calibrate the control chart (by determining the centerline and control limits), and each control chart was generated 1000 times to estimate the ARL_1 values for different shift sizes and sample sizes. The simulation parameters are listed in Table 5.6.

Table 5.6: Simulation parameters for ARL_1 performance

Parameter	**Value**
Iteration by control chart	1000
Sample sizes (n)	$[2, 3, 4, 5, 6, 7, 8, 9, 10]$
Shift sizes (z)	$[0.1, 0.2, 0.5, 1, 1.5, 2, 3]$
Shift location (i-th sample)	300
Samples to estimate control limits	30
Length of simulated TPT series	1000
Nominal ARL_0	$\sim$370
False alarm rate (α)	0.0027

For the shift size selection, I covered all the small, medium and large shift size intervals. To this end, I followed the strategy used by Muñoz et al. (2023) to specify the interval from 0 to 3. I use smaller steps for the lower section of the interval to obtain better interpretable results when the shift is more difficult to detect.

The Figure 5.3 values for different shift sizes are presented in Figure ARL_1. The colors of the lines represent the control chart type, and each section of this figure shows the calculation for a specific sample size.

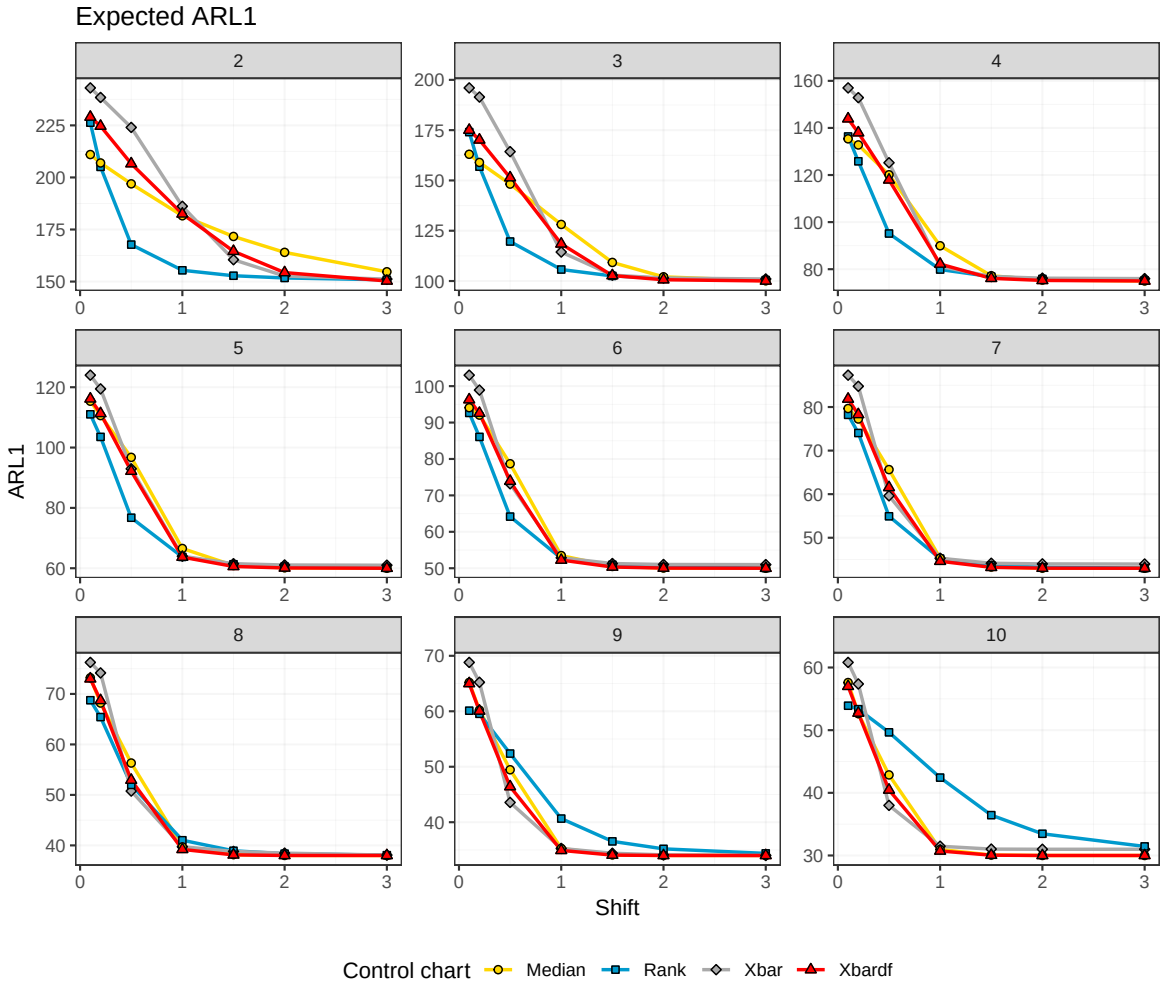


Figure 5.3: Out-of-control ARL based on the simulation

As Figure 5.3 shows, the SMR chart has the best performance, with the lowest ARL_1 value in the case of $n \leq 7$. If $n > 7$, the performance measures of the control charts approach one another regardless of the size of the shift. The shift size also has a significant influence. If the shift size is greater than one, distribution-free control charts do not have an advantage over the traditional X-bar chart. On the basis of the results, the following recommendations can be provided: To control an OP for which normality cannot be guaranteed, if the sample size is small, i.e., $n < 5$, a nonparametric control chart should be used, such as the SMR, median or distribution-free X-bar chart. For moderate sample sizes such as $5 \leq n < 8$, only the SMR chart is recommended since only this nonparametric chart has significantly better performance than the traditional X-bar chart does. Finally, for large sample sizes ($n > 7$), a nonparametric control chart does not result in better performance than the traditional X-bar chart does, regardless of the shift size. Like ARL_0, the out-of-control run weights are also analyzed with MRL_1 and $SDRL_1$, as shown in

Table 5.7.

Table 5.7: Control chart out-of-control performances

		DF X-bar		**SMR**		**Median**		**X-bar**		
n	z	MRL_1	$SDRL_1$	MRL_1	$SDRL_1$	MRL_1	$SDRL_1$	MRL_1	$SDRL_1$	Best MRL_1*
2	0.1	306.50	129.29	204.00	81.61	**193.00**	52.76	198.00	91.44	M
	0.5	190.00	84.64	**159.00**	27.95	163.50	52.92	174.00	92.42	SMR
	1	159.00	53.90	**153.00**	7.25	154.00	29.07	159.00	60.18	SMR
	1.5	153.00	27.69	**152.00**	3.15	153.00	32.83	153.00	21.06	SMR
	2	**151.00**	24.65	**151.00**	1.93	152.00	38.16	152.00	4.09	DFX, SMR
	3	**150.00**	0.94	**150.00**	1.16	150.00	9.59	151.00	0.47	DFX, SMR
3	0.1	177.50	68.58	**162.00**	60.68	177.50	71.06	173.00	67.26	SMR
	0.5	135.00	53.94	**111.00**	23.23	147.00	64.53	144.00	59.52	SMR
	1	107.00	29.06	**103.00**	7.17	111.00	40.90	107.00	17.21	SMR
	1.5	**101.00**	5.80	102.00	3.18	102.00	20.03	102.00	2.75	DFX
	2	**100.00**	1.19	101.00	1.84	101.00	10.06	101.00	0.91	DFX
	3	**100.00**	0.20	**100.00**	0.85	**100.00**	1.02	101.00	0.18	DFX, SMR, M
4	0.1	159.00	46.12	127.00	42.41	**100.00**	27.06	136.50	51.62	M
	0.5	100.00	42.45	**87.00**	22.12	101.00	43.10	111.00	43.82	SMR
	1	79.00	8.45	**78.00**	5.00	82.00	22.13	79.00	5.96	SMR
	1.5	**75.00**	1.69	76.00	2.37	76.00	5.82	76.00	1.35	DFX
	2	**75.00**	0.53	**75.00**	1.28	75.00	0.90	76.00	0.48	DFX, SMR
	3	**75.00**	0.04	**75.00**	0.56	75.00	0.00	76.00	0.06	DFX, SMR
5	0.1	127.00	30.13	**107.00**	34.57	110.00	24.36	115.00	41.46	SMR
	0.5	80.00	29.38	**70.00**	17.43	88.00	31.31	82.00	30.76	SMR
	1	**62.00**	5.58	**62.00**	4.58	63.00	11.24	**62.00**	4.01	DFX, SMR, X
	1.5	**60.00**	1.03	61.00	1.90	**60.00**	1.46	61.00	1.01	DFX, M
	2	**60.00**	0.34	**60.00**	0.88	**60.00**	0.43	61.00	0.32	DFX, SMR, M
	3	**60.00**	0.00	**60.00**	0.36	**60.00**	0.00	61.00	0.11	DFx, SMR, M
8	0.1	**63.50**	17.67	73.50	19.48	67.00	19.33	75.00	25.51	DFX
	0.5	47.00	14.84	47.00	12.62	50.00	16.21	**46.00**	12.64	X
	1	**39.00**	1.59	40.00	3.73	**39.00**	2.41	**39.00**	1.44	DFX, M, X
	1.5	**38.00**	0.38	39.00	1.33	**38.00**	0.47	39.00	0.55	DFX, M
	2	**38.00**	0.08	**38.00**	0.64	**38.00**	0.13	**38.00**	0.50	DFX, SMR, M, X
	3	**38.00**	0.00	**38.00**	0.28	**38.00**	0.00	**38.00**	0.27	DFX, SMR, M, X
10	0.1	**52.00**	16.42	53.00	16.03	57.50	17.14	59.00	20.47	DFX
	0.5	37.00	10.68	47.00	13.48	39.50	11.99	**35.00**	8.54	X
	1	**30.00**	1.06	40.00	12.26	**30.00**	1.31	31.00	0.92	DFX, M
	1.5	**30.00**	0.25	34.00	7.69	**30.00**	0.30	31.00	0.18	DFX, M
	2	**30.00**	0.00	32.00	4.04	**30.00**	0.04	31.00	0.10	DFX, M
	3	**30.00**	0.00	31.00	1.95	**30.00**	0.00	31.00	0.04	DFX, M

Nominal ARL_0 is set to ~370 ($\alpha = 0.0027$ resulting $k = 3$)
* M = Median, SMR = Standardized Mean-Rank, DFX = DF X-bar, X = X-bar

These findings have important operational implications for business process monitoring. In many real-world organizational environments, collecting large samples may be impractical because of long process durations, limited process repetition, or operational cost constraints. Under such conditions, the use of distribution-free control charts becomes especially beneficial.

Table 5.7 also confirms the observation from Figure 5.3. The X-bar and DF X-bar

charts have the best performance with greater z; however, increasing the sample size generally reduces the performance differences among the analyzed control charts if MRL_1 and $SDRL_1$ are considered measures of performance.

Overall, the simulation results provide a direct answer to Research Question 3 (Q3). Distribution-free control charts, particularly the SMR chart, demonstrate superior robustness and shift-detection capability under non-normal business process conditions, especially when sample sizes are small and process shifts are moderate.

5.2 Results on Real Dataset

To address Research Question 2 (Q2), the operational process data were first analyzed to determine whether the assumptions required for traditional parametric control charts are satisfied. Since the literature review in Chapter 2 identified non-normality as a major challenge in business process monitoring, the distributional characteristics of the TPT were examined prior to control chart implementation.

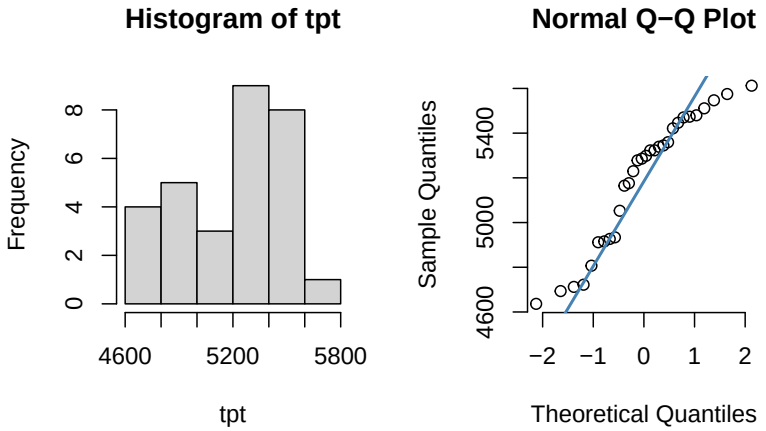


Figure 5.4: Distribution of the TPT

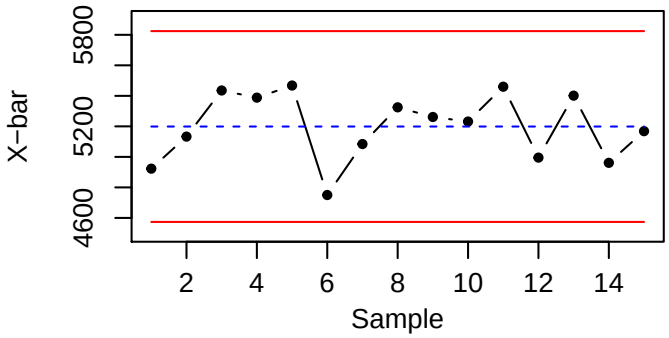
First, it is important to analyze the distribution type of the TPT as the control characteristic. The distribution of the TPT is shown in Figure 5.4.

As shown in Figure 5.4A, the histogram is skewed, which suggests that normality cannot be guaranteed during process control. The data in Figure 5.4B confirm this observation because the dots fit poorly with the Q–Q line. To statistically confirm these observations, the Shapiro–Wilk normality test is conducted via Eq. 3.11. The test statistic results in $W = 0.92$ with a significance level of $p = 0.022$; therefore, the test also confirms that the null hypothesis (the existence of a normal distribution) can be rejected and that TPT does not follow a normal distribution. This result is important from the control chart selection perspective since it indicates that traditional Shewhart

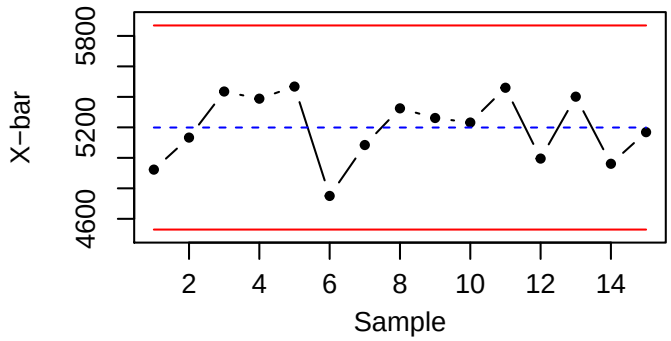
charts may not perform well because of their limitations regarding normality. Instead of focusing on these control charts, distribution-free solutions must be considered during chart selection.

This finding directly supports the concern raised in Chapter 2 regarding the applicability limitations of traditional Shewhart-type control charts in business process environments. Since the process data do not satisfy normality assumptions, the use of distribution-free monitoring approaches becomes methodologically justified.

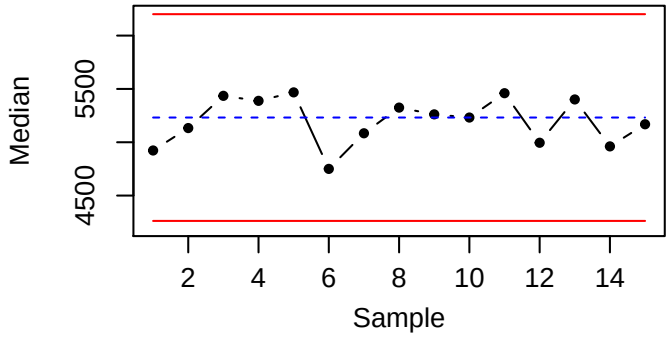
In this example, I compare the performance of multiple distribution-free control charts with that of the traditional Shewhart X-bar chart. In this work, three distribution-free control charts are tested in addition to the traditional X-bar chart: (1) the distribution-free X-bar chart (denoted as the *DF X-bar chart* below), where the control limits are calculated through permutation; (2) the median chart; and (3) the SMR control chart. Figure 5.5 shows the control charts fitted to OP.



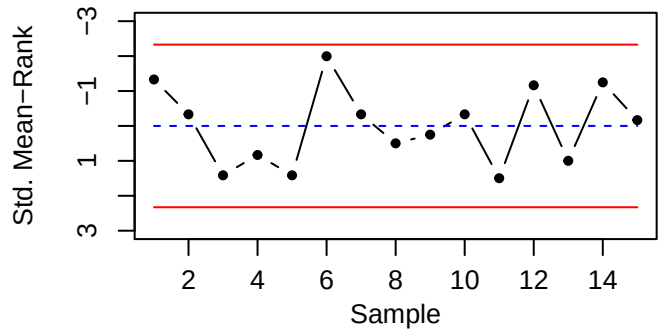
(a) X-bar chart



(b) DF X-bar chart



(c) Median chart



(d) Standardized Mean-Rank chart

Figure 5.5: Fitting control charts to monitor the TPT. The black dots represent the sample statistics, the red lines denote the UCL and LCL, and the blue dashed line is the centerline of the chart.

As Figure 5.5 shows, the control chart patterns are very similar for the X-bar, DF

X-bar and median charts (Figure 5.5A–C) and the SMR chart differs only in terms of the control chart pattern (Figure 5.5). None of the four control charts indicate an out-of-control signal; however, differences exist in the width of the acceptance interval. The DF X-bar charts show only a slight difference related to the control limit values, whereas the median chart operates with a more relaxed control strategy. The SMR chart has the strictest control interval of the control charts considered. This observation suggests that the median chart could be a good choice when the goal is to achieve the maximum ARL_0 value (strong in-control performance) and the SMR chart is the best choice for minimizing ARL_1, i.e., achieving the fastest reaction in detecting a process shift. Table 5.8 shows the exact values of the center, lower, and upper control lines of the four fitted control charts.

Table 5.8: Calculated limits of the fitted control charts

Chart	CL	LCL	UCL
X-bar	5217.49	4854.73	5580.247
DF X-bar	5199.01	4529.49	5868.54
Median	5231.69	4262.385	6201.00
SMR	0.00	-2.33	2.33

As Table 5.8 also confirms, the mean rank chart has the narrowest control interval (good for achieving a small ARL_1), whereas the median chart has the widest interval (beneficial for a high ARL_0). Nevertheless, analyzing long-term average run lengths using simulations is necessary to draw more reliable conclusions.

5.3 Control Chart Selection

Although simulation results provide detailed performance comparisons, practitioners require interpretable decision-support mechanisms for selecting appropriate control charts under operational constraints. Therefore, a decision tree analysis was conducted to transform the simulation findings into an operational chart selection framework.

This analysis represents a practical extension of the proposed methodology by converting statistical performance results into actionable process monitoring guidelines.

For a clearer presentation of the recommendations, I conducted a decision tree analysis, where the dependent variable is the control chart with the minimal ARL_1 and the independent variables are the sample size (n) and shift size (z). The resulting decision tree structure is shown in Figure 5.6.

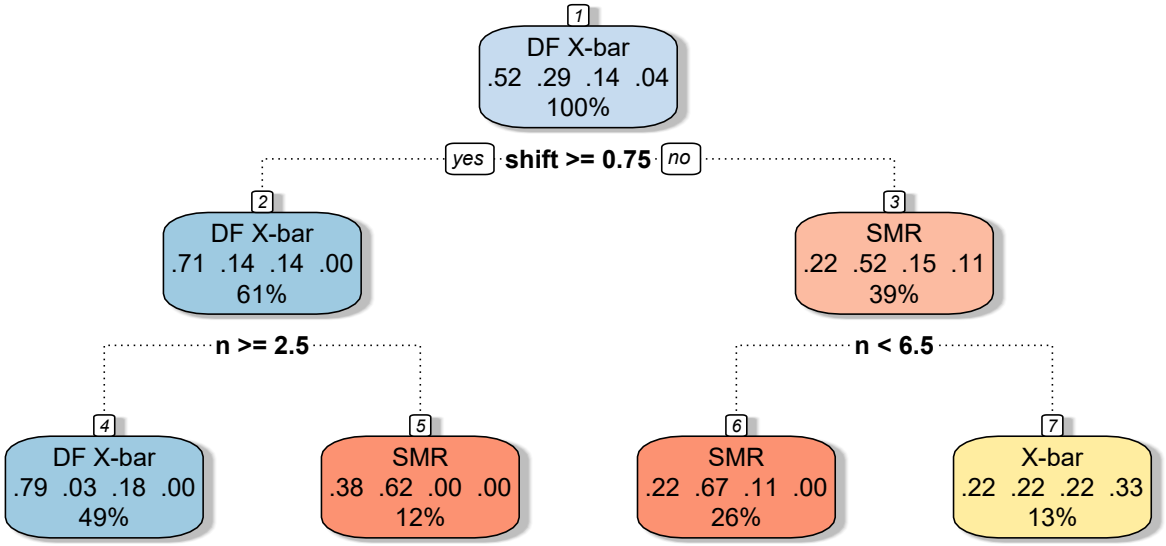


Figure 5.6: Control chart recommendations for an OP, aiming to minimize ARL_1

The characteristics of the decision tree are also worth analyzing. The error of trees of different sizes is shown in Figure 5.7. The upper x-axis shows the size of the tree (number of terminated nodes), and the lower x-axis denotes the cp score, which is a complexity measure of the tree.

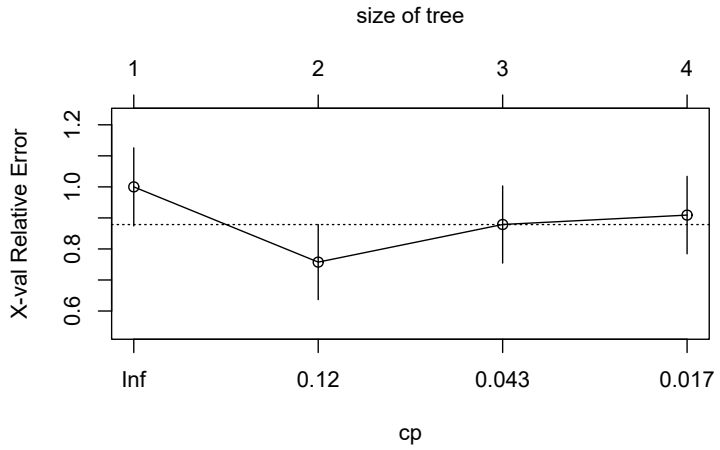


Figure 5.7: Control chart recommendations for an OP, aiming to minimize ARL_1

The algorithm uses complexity measures as stoppage criteria for tree growth. To prevent overfitting, in this case, the cp value for the current tree size is above the default stoppage value; therefore, the tree size can be accepted at a size of four since it is near the geometric mean of the cp values calculated from cross-validations, and keeping it at the greatest available depth provides more detailed insight for understanding the selection rules.

Figure 5.6 supports practitioners in the control chart selection since it shows the preferred control charts on the basis of the desired sample size and expected shift size. Each leaf of the decision tree denotes the best control chart according to the combination of the input parameters (n, z). The classification trees define the cutoff points that provide the purest classes as much as possible. To measure purity, the Gini index and entropy are measured for each split (Ferreira and Vasilyev 2015). With this strategy, the cutoff point for the shift size is 0.75. If $z > 0.75$ and at least $n = 3$ samples can be taken, the DF X-bar chart provides the best performance. If the shift size remains the same but n must be smaller because the process is long and it takes a long time to collect samples with high n, the SMR chart is recommended to obtain the lowest ARL_1. When $z \leq 0.75$ and $n < 7$, the SMR chart still has the best performance. In this small-shift scenario with a greater sample size ($n > 7$), the Shewhart X-bar chart can be used. Notably, the median chart is not shown in the decision tree in any of these cases since it performs better than the other control charts in very few special cases. Therefore, the ratio of cases where the median chart outperforms the others is negligible during the formulation of the overall control chart selection rules. A further notable observation based on the decision tree results is that in control chart selection, the shift size has greater importance than the sample size since the shift size takes a higher level in the tree hierarchy (splitting is performed starting with the independent variable that has the strongest influence on the dependent variable). This observation also suggests that in control chart selection for OPs, the shift size should be considered first. The data in Figure 5.6 confirm the observations in Figure 5.3.

In this study, the independence of the TPT values was assumed, and this assumption was supported by the absence of significant autocorrelation among the data points. However, autocorrelation could appear in OP data in several cases; in this situation, ARIMA control charts can be used (Costa and Fichera 2021, Yao et al. 2023) even if the collected data are also subject to measurement uncertainty (Sabahno 2023).

The decision tree therefore transforms the simulation findings into a practical operational framework that supports control chart selection in non-normal business process environments.

5.4 Sensitivity Analysis

The control chart performance is also analyzed when different distribution types are assumed. During the simulation, the initial distribution parameters were used, and the 3rd and 4th moments of the distribution, i.e., skewness and kurtosis, were changed stepwise to generate TPT observations. Afterward, the same ARL_1 calculation was conducted, as described in section 5.1. The Figure 5.8 values in each

chart for different combinations of skewness and kurtosis are shown in Figure ARL_1. Tests were performed under different sample sizes and shift assumptions (left side of Figure 5.8). In each contour subfigure, the color reflects the ARL_1 value for the given combination of skewness (x-axis) and kurtosis (y-axis).

Overall, the results show that the analyzed control charts are insensitive to the distribution type since the ARL_1 change is approximately 1–2 on average (see the color bars), even with a smaller sample size (n=5). The X-bar chart is the only exception, but this sensitivity also weakens if the sample size and shift size increase, which is expected because of the effect of the central limit theorem. Interestingly, the median and DF X-bar charts differ when n=5. While X-bar and SMR charts have higher ARL_1 values for symmetric distributions, the other two charts increase at extreme values for skewness and kurtosis; however, this change is still insignificant, and when $n = 10$ and $z = 2$, these control charts have very small reactions to any change in the distribution parameters. This analysis also confirms that the selected control charts are good choices for monitoring OPs since they are robust to changes in the distribution parameters.

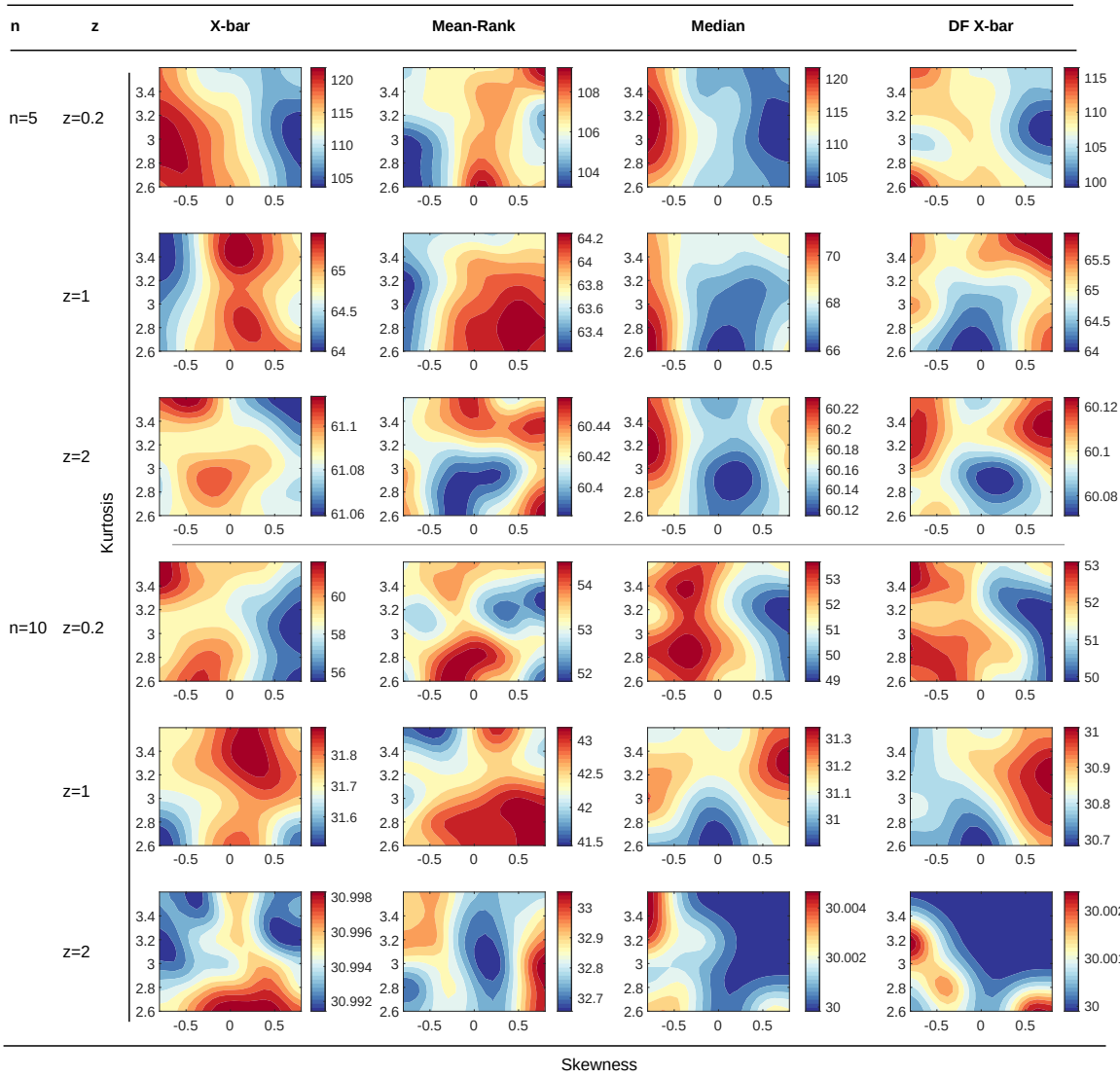


Figure 5.8: Control chart recommendations for an OP, aiming to minimize ARL_1

The sensitivity analysis demonstrates that the analyzed distribution-free control charts remain highly robust under varying skewness and kurtosis conditions. This robustness is particularly valuable in operational process environments where process distributions may evolve dynamically over time.

These findings further support the suitability of distribution-free monitoring approaches for practical business process applications.

5.5 Chapter Summary

This chapter evaluated the performance of traditional and distribution-free control charts within a business process monitoring environment characterized by non-normal operational data.

The findings demonstrated that:

- the operational process data violate normality assumptions,
- distribution-free control charts outperform traditional Shewhart charts under small sample conditions,
- and the performance differences diminish as sample size increases because of the effect of the central limit theorem.

Among the analyzed approaches, the SMR chart consistently achieved superior shift-detection capability for small and moderate sample sizes, while the DF X-bar chart demonstrated competitive performance for larger shifts and larger samples.

The results directly answer Research Questions 2 (Q2) and 3 (Q3) by confirming that:

1. non-normality significantly affects control chart performance in business process environments, and
2. distribution-free monitoring approaches provide superior robustness and operational effectiveness under these conditions.

Furthermore, the decision tree framework transforms the simulation findings into a practical chart selection methodology, thereby extending the contribution of this research from theoretical performance evaluation toward operational decision support.

The findings also contribute to the broader literature on economic-related statistical process control by extending control chart evaluation from traditional manufacturing systems toward operational business process environments characterized by heterogeneous and non-normal process behavior.

The implications of these findings are discussed in Chapter 6.

Chapter 6

Summary and Conclusion

This chapter summarizes the most important academic findings of the dissertation. Section 6.1 assesses the research proposals introduced in the Chapter 1. Section 6.2 details theoretical, methodological, and practical contributions to the existing scientific literature. Section 6.3 looks into managerial implications and limitations, followed by potential directions for future research in Section 6.4 and the final concluding reflections in Section 6.6.

6.1 Evaluation of Research Proposals

This dissertation investigated the integration of Economic-related Statistical Process Control (ESPC) within BPM environments, with particular emphasis on the monitoring of non-normal business process data. The study addressed three research questions related to the industrial application of ESPC, the behavior of control charts under non-normal conditions, and the performance of a proposed distribution-free control chart framework for business processes.

6.1.1 Evaluation of Proposal P1

P1: *Economic-related statistical process control (ESPC) charts will be considered mostly in the manufacturing industry compared to the non-manufacturing industries.*

The findings of the systematic literature review confirmed Proposal P1. The review demonstrated that ESPC applications remain heavily concentrated within manufacturing industries, particularly in the food, automotive, chemical, and mechanical sectors. Most identified studies focused on production-oriented quality management problems where statistical process control techniques have traditionally been applied.

In contrast, only a limited number of studies investigated ESPC applications in service-oriented or organizational business processes. The findings therefore reveal

a substantial research imbalance between manufacturing and non-manufacturing environments. Furthermore, the review showed that existing ESPC studies rely predominantly on parametric assumptions, particularly normal distributions, despite the increasing prevalence of complex and non-normal operational data in modern organizations.

These findings highlight an important research gap and justify the need for extending SPC methodologies beyond conventional manufacturing systems into broader business process environments.

6.1.2 Evaluation of Proposal P2

P2: *The performance evaluation of the BP control chart under non-normality conditions reveals its effectiveness in detecting process deviations and facilitating timely corrective actions.*

The empirical and simulation results supported Proposal 2 (P2). The study demonstrated that business process data frequently violate the normality assumptions underlying traditional parametric control charts because of skewness, heavy tails, multimodality, and operational variability. Despite these challenges, the integration of control charts within EPC-modeled business processes proved effective for monitoring operational performance and detecting process deviations.

The results further indicated that nonparametric and distribution-free approaches maintain more stable in-control behavior under non-normal conditions compared to traditional Shewhart-type charts. The proposed monitoring framework therefore enables statistically reliable process supervision even when the underlying process distributions cannot be accurately specified.

The findings confirm that statistical process control methodologies can be successfully adapted for business process environments and can support real-time operational quality assurance in non-manufacturing contexts.

6.1.3 Evaluation of Proposal P3

P3: *The proposed distribution-free BP control chart will demonstrate significantly lower out-of-control Average Run Length (ARL_1) values compared to traditional parametric charts when detecting small-to-moderate shifts in non-normal processes.*

Proposal P3 was also confirmed by the simulation experiments. The proposed distribution-free business process control chart consistently achieved improved out-of-control detection performance across multiple non-normal distribution scenarios and varying sample sizes.

The simulation results showed that traditional parametric control charts experienced considerable performance degradation when normality assumptions were

violated. In contrast, the proposed distribution-free methodology maintained stable in-control performance while achieving lower ARL_1 values for small-to-moderate process shifts. The proposed framework demonstrated particular robustness under skewed and heavy-tailed distributions, which are common characteristics of operational business process data.

These findings establish the practical suitability of distribution-free monitoring approaches for business process applications where traditional SPC assumptions are unrealistic or difficult to verify.

6.2 Contributions to Literature

This dissertation contributes to the literature in theoretical, methodological, and practical dimensions.

6.2.1 Theoretical Contributions

The dissertation contributes to the theoretical development of ESPC by establishing a structured understanding of how economic considerations have been incorporated into statistical process control research. Through the systematic literature review, the study identified dominant ESPC design approaches, methodological limitations, industrial application patterns, and distributional assumptions used within the existing body of research.

The proposed Theoretical codification criterion (TCC) provides a structured framework for classifying ESPC studies according to economic models, control chart types, process validation approaches, probability distributions, and industrial applications. This classification contributes to the conceptual organization of ESPC research and highlights important research gaps, particularly the limited extension of ESPC into business process environments.

The dissertation also contributes theoretically by extending SPC concepts beyond traditional manufacturing systems into organizational and service-oriented business processes. The study demonstrates that the principles of statistical monitoring can be integrated with business process management frameworks to support operational quality assurance in dynamic business environments.

6.2.2 Methodological Contributions

The principal methodological contribution of this dissertation is the development and evaluation of a distribution-free control chart framework designed specifically for business process monitoring under non-normal conditions.

Traditional SPC methodologies generally assume normally distributed observations, an assumption that is rarely satisfied in operational business environments. The proposed framework addresses this limitation by employing distribution-free monitoring techniques that remain statistically valid regardless of the underlying process distribution.

The dissertation further contributes methodologically through the integration of Event-Driven Process Chain (EPC) modeling with statistical monitoring approaches. This integration establishes a systematic procedure for identifying process control points, embedding monitoring mechanisms within operational workflows, and supporting event-driven quality control strategies.

Additionally, the study contributes to the methodological literature on control chart evaluation by systematically comparing traditional and nonparametric approaches across varying sample sizes, shift magnitudes, and distributional conditions. The simulation-based validation framework provides a comprehensive basis for evaluating monitoring performance under realistic operational scenarios.

6.2.3 Practical Contributions

From a practical perspective, the dissertation provides organizations with a framework for implementing statistically robust and economically meaningful monitoring systems in business process environments.

The findings demonstrate that SPC methodologies can be effectively applied within service-oriented and administrative operations such as healthcare, finance, logistics, customer service, and other organizational processes where process data frequently exhibit non-normal characteristics.

The integration of EPC modeling and control charts enables managers to identify critical process stages, establish targeted monitoring points, and improve process transparency. The proposed distribution-free framework further reduces the risks associated with false alarms and missed detections that often arise when traditional parametric control charts are applied to non-normal business data.

Consequently, the dissertation contributes practical guidance for improving operational quality management, supporting process improvement initiatives, and enhancing decision-making within modern organizations.

6.3 Managerial Implications and Limitations

The findings of this dissertation carry important implications for managers, quality engineers, and operational decision-makers.

First, the research demonstrates that business processes can be monitored using

SPC methodologies even when classical statistical assumptions are violated. This is particularly relevant for modern organizations operating in highly dynamic environments characterized by irregular process behavior and heterogeneous operational data.

Second, the integration of EPC-based process modeling with statistical monitoring supports real-time operational visibility and process transparency. Managers can utilize the proposed framework to identify process deviations early, reduce operational inefficiencies, and improve service quality performance.

Third, the findings emphasize the importance of incorporating economic considerations into process monitoring design. Monitoring systems should not only provide statistical sensitivity but should also minimize operational losses associated with process deviations, false alarms, and delayed interventions.

Despite these contributions, several limitations should be acknowledged.

The first limitation concerns the empirical scope of the validation process. Although the dissertation combined real-life case studies with extensive simulation experiments, the practical validation was limited to a relatively narrow set of operational environments. Additional empirical applications across multiple industries would improve the generalizability of the findings.

The second limitation relates to the focus on univariate process monitoring. Many organizational environments involve complex multivariate dependencies among operational variables that were not fully addressed within this study.

Another limitation concerns computational complexity. Advanced distribution-free and adaptive monitoring techniques may require greater computational resources and statistical expertise than traditional SPC approaches, potentially limiting implementation in smaller organizations.

Finally, while the dissertation emphasized economic-related process monitoring, the economic evaluation remained partially conceptual because of limited access to detailed organizational cost structures and operational financial data.

6.4 Future Research Directions

This dissertation opens up various avenues for further research. First, this proposed system may be extended to multivariate business process monitoring by future researches, which will enable the monitoring of various indicators at the same time and the interaction among different indicators.

Secondly, combining the application of machine learning, artificial intelligence with that of SPC approaches will bring great benefits in adaptive and predictive business process monitoring. Our future works could focus on intelligent control chart systems which could automatically tune the monitoring settings by user-specified

current system states.

Third, in the future, more research would look at combining process mining / digital process analytics with statistical monitoring systems based on EPCs. It would assist automated detection of abnormal process states or process optimization in a data self-sufficient organization. Further potential research avenues lie in integrating automatic real-time monitoring functionalities into enterprise information systems and Industry 4.0 infrastructures. The increasing abundance of operating data streams seems well suited for constant quality monitoring and automatic process control.

Lastly, more empirical research in various industries and organizations studies would be helpful to further testify the present model and to develop industry-specific implementation guideline.

6.5 Summary

My thesis investigated the integration with BPM in order to address limitations in existing process monitoring research. The study was motivated by the observation that most ESPC studies focus primarily on manufacturing environments and rely heavily on parametric assumptions, particularly the assumption of normally distributed process data. However, business process environments frequently generate skewed, dynamic, and non-normal data, making traditional SPC techniques less reliable for modern business applications.

To address these limitations, I explored the applicability of SPC techniques within business process environments through the use of EPC modeling. Furthermore, the study examined the performance limitations of traditional control charts under non-normal process conditions and proposed a distribution-free OP control chart capable of operating without strict distributional assumptions.

The research combined systematic literature review, methodological development, simulation experiments, and practical operation process applications. The results demonstrated that existing ESPC research provides limited attention to business process environments and insufficient consideration for distribution-free monitoring approaches. The proposed methodology showed improved robustness and enhanced detection capability under skewed and non-normal process distributions, thereby supporting more reliable business process monitoring and decision-making. As the outcome of the dissertation, three theses were defined:

Thesis 1: The Systematic Literature Review shows that the research of the Economic-related Statistical Process Control is mostly focused on manufacturing industries and is highly dependent on parametric assumptions, especially normality. The review also found that Economic-related Statistical Process Con-

trol was only used to a limited extent in service-oriented and business process environments. These results suggest a research gap regarding the extension of Economic-related Statistical Process Control from traditional manufacturing environments to non-manufacturing and business process environments.

Thesis 2: A distribution-free Operation Process control chart was developed and evaluated within the framework of this research. The proposed monitoring approach does not rely on strict distributional assumptions and demonstrated improved robustness and monitoring stability under non-normal process conditions. The results showed that the proposed method provides more reliable monitoring performance compared to traditional parametric control charts, particularly under skewed distributions and varying process conditions.

Thesis 3: The suggested distribution-free Business Process control chart detection of out-of-control conditions was superior in non-normal process situations with various sample sizes and shift sizes. Specifically, the proposed method obtained smaller out-of-control average run length (ARL1) values for small to moderate process shifts, showing its effectiveness in detecting the process changes in non-normal business processes compared to the traditional parametric control charts.

In addition to the three thesis-level findings, the dissertation provides a methodological framework that integrates Event-driven Process Chain (EPC) modeling with Statistical Process Control. The EPC representation enables business processes to be structured into identifiable process activities and provides a basis for determining where statistical monitoring can be applied. This integration supports the practical implementation of the monitoring approaches investigated in Theses 2 and 3 and facilitates the extension of SPC from traditional manufacturing processes to business process environments.

6.6 Conclusion

This thesis extends a line of work in a cross-disciplinary environment that shows a possibility and benefits of implementing statistically sound, economically meaningful monitoring system in some operational situations other than manufacturing. The research confirmed that the state-of-the-art on ESPC studies is largely to targeted at manufacturing use and showcases ever-growing reliance on parametric assumptions that tend to be impractical in today's business process environment.

To this end, the dissertation proposed and tested a distribution-free monitoring

approach that could sustain the desired performance under non-normal process environment.

The results of the study also suggest that the combination of SPC approaches and EPC-centered business process modeling is a promising combination for operational quality management, process transparency and real-time process performance control. In addition, in the application to non-normal business process data the developed distribution-free control chart outperformed the classical parametric control chart for robustness and shift detection strength.

Generally, the dissertation is contributing towards the transition of SPC from a statistic quality tool designed for manufacturing companies into an all-encompassing organizational performance management approach, adapted to the new demands of the information age. My research results were published in the following international scientific papers:

Thesis 1 **:** Kosztyán, Z. T., MacClever, A. B., and Katona, A. I. (2026). Economic-related Statistical Process Control Charts and Industrial Applications: A Systematic Literature Review. (**under journal review**)

Thesis 2 **and** 3 **:** Kosztyán, Z. T., MacClever, A., Khan, Z., Hegedűs, C., Saghir, A., Csizmadia, T., and Katona, A. I. (2026). Advancing process monitoring: a distribution-free control framework for operation processes. Computers in Industry, 177, 104449. DOI: doi.org/10.1016/j.compind.2026.104449

Glossary

ESPC Economic-related Statistical Process Control. 25

Acronyms

AC Analytical Complexity. 20, 21, 36

ARL Average Run Length. 10, 31, 32, 35, 37, 51

BPM Business Process Management. 8, 27, 36, 79, 84

CC Control Chart. 17, 18, 22–25

CUSUM Cumulative Sum. 8, 30, 33, 35, 36, 47

ED Economic Design. 16–18, 20–22, 35

EPC Event-Driven Process Chain. 28–30, 36–42, 47–49, 80, 82–86, 91

ERP Enterprise Resource Planning. 51

ESD Economic Statistical Design. 17, 18, 20–22, 35, 36

ESPC Economic-related Statistical Process Control. 9, 12, 14, 15, 17, 18, 20–25, 27, 35–39, 79–81, 84, 85

EWMA Exponentially Weighted Moving Average. 8, 30, 33, 36, 47

FAP False Alarm Probability. 44–46

IC Implementation Challenges. 20, 21

LA Limited Data Availability. 20, 36

MA Modeling Assumptions. 20, 21, 36

MSPC Multivariate Statistical Process Control. 7, 8

OP Operation Process. 9, 37, 44, 47–51, 53, 56, 60, 62, 68, 71, 74, 75, 77, 84, 91

PE Parametric Estimation. 20, 21, 36

RBD Risk-based Design. 17, 18, 20–22, 35, 36

SLR Systematic Literature Review. 7, 12, 15, 18, 27, 35, 37

SMR Standardized Mean–Rank. 44–46, 65, 66, 68, 70, 71, 73, 75, 76, 78, 94

SPC Statistical Process Control. 7–9, 37, 80–86

TCC Theoretical Codification Criterion. 15, 17, 18, 37, 81

TPC Total Process Cost. 48–51

TPT Total Process Time. 8, 48–51, 53, 54, 58–60, 62, 64, 70

UML Unified Modeling Language. 29

Appendix A
Detailed task descriptions related to the maintenance process

Table 6.1: Description of each task in the operational process

Task	Description
t_1	Production is stopped.
t_2	Maintenance personnel are called to inspect the machine.
t_3	The cause of the error is determined.
t_4	The production manager notifies the management.
t_5	The management assigns the task to the procurement manager.
t_6	It is ascertained whether the machine is under warranty.
t_7	A price quote is requested from the machine's manufacturing company by procurement.
t_8	The request for a price quote is received by the manufacturing company.
t_9	Experts from the manufacturing company are sent to the company to assess the nature of the error.
t_{10}	Following the assessment, the findings are summarized, and a price quote for the repair costs is sent.
t_{11}	Procurement informs the company's management regarding the price quote.
t_{12}	A decision is made concerning the price quote.
t_{13}	The price quote is negotiated with the supplier.
t_{14}	The price quote is accepted.
t_{15}	The manufacturing company is notified of the acceptance of the price quote, and the contract is concluded.
t_{16}	The manufacturing company commences the execution of the assignment.
t_{17}	The malfunctioning machine is transported to the manufacturing company.
t_{18}	The repair of the machine and the replacement of parts are initiated by the experts.
t_{19}	Trial production is conducted on the repaired machine.
t_{20}	Quality is checked by the responsible inspector.
t_{21}	The cause of the error is examined.
t_{22}	The product is manufactured again.
t_{23}	The repaired machine is transported to the production company.
t_{24}	The faulty machine is returned to the company providing the warranty.
t_{25}	The new machine is returned by the suppliers.
t_{26}	The machine is taken into the company's inventory.
t_{27}	Procurement is notified about it.
t_{28}	Procurement informs the warehouse staff and maintenance personnel.
t_{29}	The machine is repaired on-site by the experts.
t_{30}	The machine is put into operation.
t_{31}	Trial production is performed on the machine.
t_{32}	The machine is put back into production.
t_{33}	The fulfillment of orders is resumed.
t_{34}	The rectification of the error is checked by management.
t_{35}	The invoice is paid.
t_{36}	Production returns to its state prior to the error.

Appendix B

Other examples for real-world applications: Human resource recruitment process

Although the usage of the proposed methods is independent of OP, in this section, the application of control charts for operation processes is demonstrated in a more general real-world business process, the recruitment and selection of white-collar human resources, which is performed similarly in several industries. The examined process (see the EPC in Figure 6.1) has 30 tasks with 3 decision points, such as *'Choosing the recruitment methods and cohorts'* ($T9$) and then *'Choosing internal succession and replacement plans'* ($T10$) or *'Selection of external recruitment methods and channels'* ($T14$), and several parallel task executions. The whole process starts with *'Identifying a gap between needed and available human resources'* and ends with *'Selecting the most suitable applicant (to eliminate the discrepancy)'*. None of the 30 tasks have normally distributed durations, and since costs depend mostly on the amount of time spent working, costs also do not follow a normal distribution.

All 30 tasks of the recruitment process are listed in Table 6.2.

Table 6.2: Description of each task in the recruitment process

Task	Description
T1	Identifying a gap between needed and available human resources
T2	Labor demand is assessed
T3	Analysis of labor utilization
T4	Labor requirement calculation
T5	Decision about required headcount and initiation of requirement process
T6	Analysis of the job specifications for a given position
T7	Job descriptions are compiled based on job specifications
T8	Preparing for recruitment, listing applicable methods
T9	Choosing the recruitment methods and cohorts
T10	Choosing internal succession and replacement plans
T11	Consultation with all managers concerned
T12	Consultation with employees (candidates/affected parties)
T13	Development of required plans
T14	Selection of external recruitment methods and channels
T15	Establishing contact with the appropriate entities
T16	Development of the background for external recruitment and the necessary tools
T17	Creating job advertisements based on the job descriptions
T18	Posting the advertisements and sending them for publishing
T19	First filtering of candidates
T20	Suitable candidates are invited for an interview
T21	Unsuitable candidates are informed of their unsuccessful application
T22	Booking a meeting room
T23	Informing the reception about the arrival of new people
T24	Preparing an interview schedule
T25	Arrival and reception of interviewees
T26	Interviewing
T27	The HR department receives and administers CVs
T28	Selecting the most suitable applicant (to eliminate the discrepancy)
T29	Notification of rejected candidates
T30	Notification of selected candidate

The taskwise distributions of the standardized durations are shown in Figure. 6.2.

Similar to the maintenance process, the normality if not fulfilled by the taskwise distributions in this example is also confirmed by Figure. 6.2. The fitted control

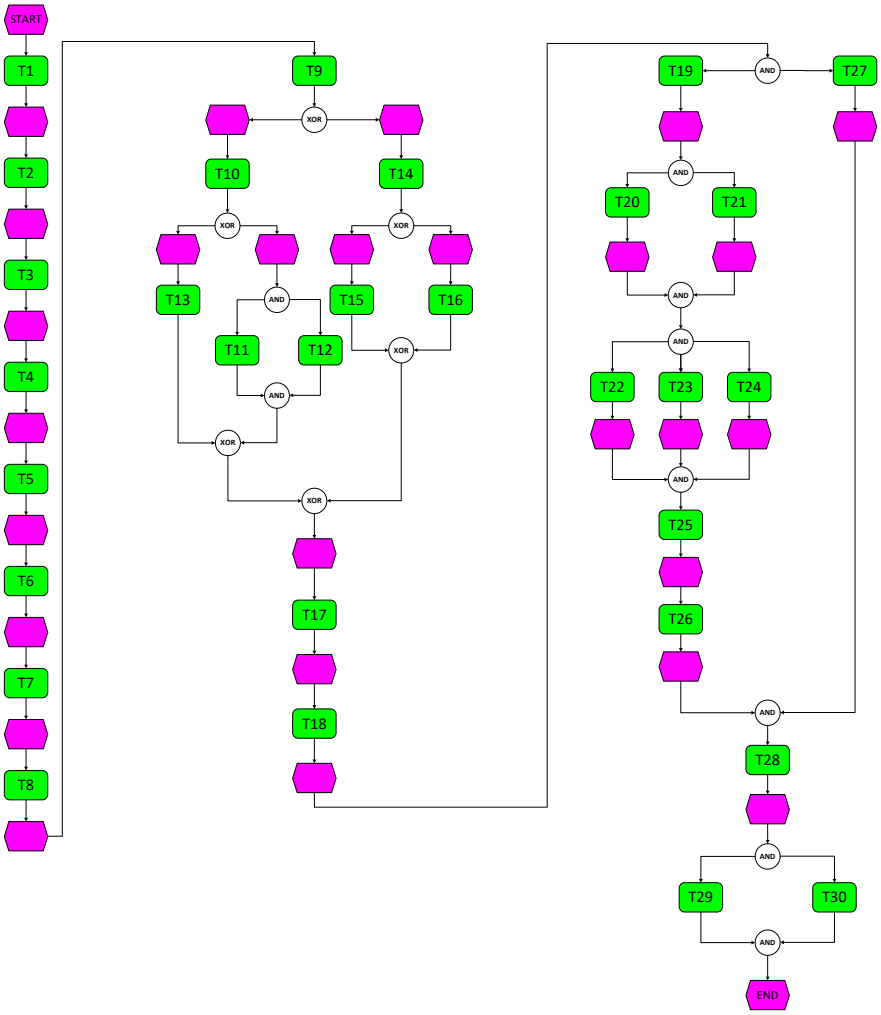


Figure 6.1: EPC model of the recruitment process in the case of organizational change

charts for monitoring the overall process 6.3 are shown in Figure. TPT. During chart fitting, 50 samples were collected, and the sample size was chosen as $n = 2$. The reason behind this choice is also technical in this case, since the opportunity for data collection is infrequent (compared with the maintenance process) in this case, and a small sample size is preferred to ensure an adequate number of sample points during the control.



Figure 6.2: Distribution of standardized durations for each task in the recruitment process

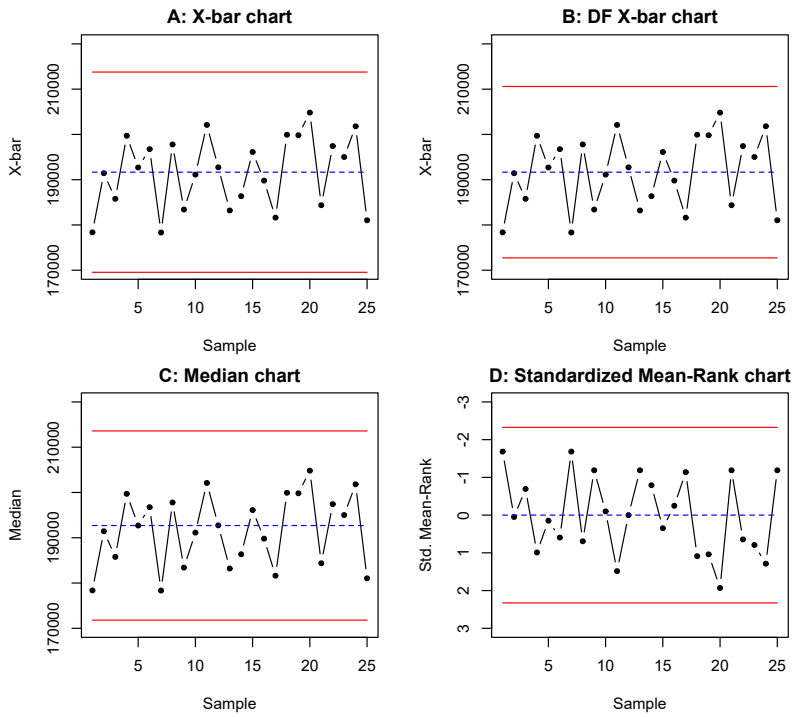


Figure 6.3: Control charts fitted for the recruitment process considering *TPT* as the control variable

As the chart patterns and control line positions suggest, the SMR chart is a good candidate for early detection of process shifts because it has the narrowest control interval. To analyze the more detailed control chart behavior under different shift sizes, the same simulation is conducted as presented in subsection 5.1. The parameter setting is also the same as that presented in Table 5.6. Table 6.3 shows the results of the simulation.

Table 6.3: Control chart performances on the human resource recruitment process ($n = 2$)

Metric	z	Chart				Best Chart*
		DF X-bar	SMR	Median	X-bar	
ARL_1	0.5	92.21	**27.91**	124.74	129.80	SMR
	1	52.51	**6.55**	79.69	87.85	SMR
	1.5	6.20	**3.68**	38.00	7.99	SMR
	2	**2.44**	2.58	8.99	4.71	DFX
	3	**1.18**	1.95	5.62	2.34	DFX
MRL_1	0.5	22.00	**13.00**	22.00	42.00	SMR
	1	12.00	**4.50**	9.00	17.00	SMR
	1.5	**3.00**	**3.00**	5.00	4.00	SMR/DFX
	2	**1.50**	2.00	2.00	3.00	DFX
	3	**1.00**	**1.00**	**1.00**	2.00	SMR/DFX/M
$SDRL_1$	0.5	167.53	**45.81**	211.96	216.32	SMR
	1	125.19	**7.37**	214.35	197.74	SMR
	1.5	10.27	**3.00**	116.15	11.07	SMR
	2	2.88	**1.93**	18.26	5.23	SMR
	3	**0.58**	1.55	24.20	0.71	DFX

Nominal ARL_0 is set to ~370 ($\alpha = 0.0027$ resulting $k = 3$)
*M = Median, SMR = Standardized Mean-Rank, DFX = DF X-bar, X = X-bar

As Table 6.3 shows, the SMR chart is suggested for use when $z < 2$; otherwise, the DF X-bar chart is the adequate choice. As the results for this practical example show, distribution-free control charts are preferred for use in each case compared with the X-bar chart.

Appendix C

Information for each article: year of publication, authors, journal and authors' country of origin

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A01	Koo and Case	1990	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	Taiwan & USA	1						
A02	Parkhideh and Parkhideh	1996	IIE TRANSACTIONS	USA		1					
A03	Chou et al.	2000	JOURNAL OF APPLIED STATISTICS	Taiwan			12				
A04	Chou et al. (a)	2001	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							
A05	Chou et al. (b)	2001	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							
A06	Jalote and Saxena	2002	IEEE TRANSACTIONS ON SOFTWARE ENGINEERING	India							
A07	Liu et al.	2002	JOURNAL OF LOSS PREVENTION IN THE PROCESS INDUSTRIES	Taiwan							
A08	Love and Linderman	2003	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	USA							
A09	Liu et al.	2003	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							
A10	Chen and Yu	2003	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							
A11	Yang	2003	COMMUNICATIONS IN STATISTICS-SIMULATION AND COMPUTATION	Taiwan							
A12	Chen	2003	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A13	Zempleni et al.	2004	APPLIED STOCHASTIC MODELS IN BUSINESS AND INDUSTRY	Hungary & Portugal							
A14	Yu and Wu	2004	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan							
A15	Yang	2005	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Taiwan				10			
A16	Garcia-Diaz and Aparisi	2005	IIE TRANSACTIONS	Spain							
A17	Yang and Rahim	2005	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	Canada & Taiwan							
A18	Yang and Rahim	2006	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	Taiwan & Canada							
A19	Ho et al.	2007	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	Brazil							
A20	Nikolaidis et al.	2007	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Greece							
A21	Wu et al.	2009	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	Singapore & USA							
A22	Ho et al.	2009	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	Brazil							
A23	Torng et al.	2009	EXPERT SYSTEMS WITH APPLICATIONS	Taiwan							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A24	Kooli and Limam	2009	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Tunisia							
A25	Chen and Yeh	2010	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Taiwan					15		
A26	Huang and Chen	2010	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Taiwan							
A27	Faraz et al.	2010	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	Iran & USA							
A28	Nil et al.	2010	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	India							
A29	Celano et al.	2011	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	Italy & Brazil							
A30	Kooli and Limam	2011	SEQUENTIAL ANALYSIS-DESIGN METHODS AND APPLICATIONS	Tunisia							
A31	Faraz and Saniga	2011	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	USA & Iran							
A32	Seif et al.	2011	JOURNAL OF APPLIED STATISTICS	Belgium & Iran							
A33	Faraz et al.	2012	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Belgium, Iran & USA							
A34	Lee et al.	2013	EUROPEAN JOURNAL OF INDUSTRIAL ENGINEERING	Taiwan							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A35	Mohammadian and Amiri	2013	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Iran							
A36	Kuo and Chu	2013	INTERNATIONAL JOURNAL OF PRECISION ENGINEERING AND MANUFACTURING	Taiwan							
A37	Celano et al.	2014	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Italy, Belgium & USA							
A38	Faraz et al.	2014	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	Belgium, USA & Brazil							
A39	Sitt et al.	2014	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Malaysia, UAE & Taiwan							
A40	Seif et al.	2015	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	Iran, Belgium & USA						12	
A41	Huang and Lu	2015	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	Taiwan							
A42	Amiri et al.	2015	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	Iran							
A43	Kosztyan and Katona	2016	EXPERT SYSTEMS WITH APPLICATIONS	Hungary							
A44	Park et al.	2017	TOTAL QUALITY MANAGEMENT & BUSINESS EXCELLENCE	South Korea							
A45	Zhou et al.	2017	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	China							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A46	Rafie et al.	2017	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Iran							
A47	Nenes	2018	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Greece							
A48	Tasias and Nenes	2018	QUALITY TECHNOLOGY AND QUANTITATIVE MANAGEMENT	Greece							
A49	Tasias and Nenes	2018	APPLIED MATHEMATICAL MODELLING	Greece							
A50	Pedro et al.	2019	TECHNOMETRICS	Brazil							
A51	Nadreri et al.	2019	INTERNATIONAL JOURNAL OF QUALITY & RELIABILITY MANAGEMENT	Iran							
A52	Zheng et al.	2020	PROCEEDINGS OF THE INSTITUTION OF MECHANICAL ENGINEERS PART B-JOURNAL OF ENGINEERING MANUFACTURE	China							20
A53	Wang and Li	2020	ANNALS OF OPERATIONS RESEARCH	Taiwan							
A54	Shamsuzzaman et al.	2021	APPLIED ENERGY	UAE, Finland, China, Egypt & Australia							
A55	Naderi et al.	2021	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Iran							
A56	Prata et al.	2021	INTERNATIONAL JOURNAL OF QUALITY & RELIABILITY MANAGEMENT	Brazil							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A57	Zheng et al.	2023	QUALITY TECHNOLOGY AND QUANTITATIVE MANAGEMENT	Saudi Arabia							
A58	Katona et al.	2023	IEEE ACCESS	Hungary & Pakistan							
A59	Saadatmellia et al.	2023	FLUCTUATION AND NOISE LETTERS	Iran							
A60	Haridy et al.	2023	SCIENTIFIC REPORTS	UAE, Egypt, Hong Kong & Saudi Arabia							
A61	Tavakoli and Heydari	2023	COMMUNICATIONS IN STATISTICS - THEORY AND METHODS	Iran							
A62	Pasha et al.	2023	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	Canada							
A63	Salmasnia et al.	2024	COMPUTERS & INDUSTRIAL ENGINEERING	Iran & Oman							
A64	Jafarian-Namin et al.	2024	SCIENTIA IRANICA	Iran							
A65	Kalisetti et al.	2024	JOURNAL OF THE INSTITUTION OF ENGINEERS (INDIA): SERIES C	India							
A66	Shojaee et al.	2024	COMPUTERS AND INDUSTRIAL ENGINEERING	Iran & Germany							
A67	Sandeep and Ranjan Mukhopadhyay	2024	COMMUNICATIONS IN STATISTICS: SIMULATION AND COMPUTATION	India							
A68	Shi et al.	2024	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	China							
A69	Lee and Chou	2024	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	Taiwan							

Table 6.4: Information for each article: year of publication, authors, journal and authors' country of origin*(continued)*

id#	Authors	Year	Journal	Country	Number of articles per period						
					1990 - 1994	1995 - 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 - 2019	2020 - 2024
A70	Shojaee et al.	2024	JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION	Iran & Germany							
A71	Sandeep and Mukhopadhyay	2024	COMMUNICATIONS IN STATISTICS-THEORY AND METHODS	India							

Appendix D

Table 6.5: Summary of the reviewed studies according to economic model, control-chart design and application characteristics.

ID	Ref.	Economic model										CD	CT	PD	AS	IA
		DCM	LVCM	BRCM	TLF	CRCM	KKCM	GWCM	BCM	ALF	CMM	UEM					
A01	Koo and Case (1990)	✓											ED	$\bar{X}$	Exponential	M	Chemical
A02	Parkhideh and Parkhideh (1996)	✓											ED	$\bar{X}$	Exponential	S	Information Techonology
A03	Chou et al. (2000)									✓			ESD	$\bar{X}$	Burr	M	Food
A04	Chou et al. (2001a)	✓											ED	$\bar{X}$	Normal	M	Food
A05	Chou et al. (2001b)	✓											ESD	$\bar{X}$	Burr	M	Mechanical Parts
A06	Jalote and Saxena (2002)											✓	ED	$\bar{X}$	Normal	S	Information Techonology
A07	Liu et al. (2002)	✓											ED	$\bar{X}$	Multivariate Normal	M	Food
A08	Love and Linderman (2003)		✓										ED	EWMA	Exponential	S	Health
A09	Liu et al. (2003)							✓					ED	$\bar{X}$	Exponential	M	Food
A10	Chen and Yu (2003)		✓										ED	MA	Normal	M	Chemical
A11	Yang (2003)			✓									ESD	$\bar{X}$	Normal	M	Textile
A12	Chen (2003)								✓				ESD	$\bar{X}$	Burr	M	Food
A13	Zempleni et al. (2004)										✓		ED	$\bar{X}$, CUSUM	Exponential	M	Pulp and Paper
A14	Yu and Wu (2004)		✓										ED	MA	Normal	M	Chemical
A15	Yang (2005)												ED	$\bar{X}$, CAUSE-SELECTING	Exponential	M	Textile
A16	Garcia-Diaz and Aparisi (2005)												ED	EWMA	Normal	M	Undefined
A17	Yang and Rahim (2005)			✓									ED	HotellingT^2	Weibull	M	Pulp and Paper
A18	Yang and Rahim (2006)			✓									ED	HotellingT^2	Multivariate Normal	M	Pulp and Paper
A19	Ho et al. (2007)				✓								ED	$\bar{X}$	Normal	M	Electronic
A20	Nikolaidis et al. (2007)										✓		ED	$\bar{X}$	Normal	M	Tiles
A21	Wu et al. (2009)											✓	ED	NP_x	Normal	M	Automotive
A22	Ho et al. (2009)				✓								ED	$\bar{X}$	Normal	M	Textile
A23	Torng et al. (2009)		✓										ED	$\bar{X}$	Normal	M	Electronic
A24	Kooli and Limam (2009)											✓	ED	NP	Binomial, Exponential	M	Tiles
A25	Chen and Yeh (2010)	✓											ED	$\bar{X}$	Gamma	M	Food
A26	Huang and Chen (2010)		✓										ED	MAX	Normal	M	Food
A27	Faraz et al. (2010)		✓										ED	HotellingT^2	Multivariate Normal	M	Automotive
A28	Nil et al. (2010)											✓	ESD	$\bar{X}$	Pareto	M	Chemical
A29	Celano et al. (2011)											✓	ED	$\bar{X}$	Reyleigh	M	Mechanical Parts
A30	Kooli and Limam (2011)	✓											ED	NP	Binomial	M	Tiles
A31	Faraz and Saniga (2011)		✓										ESD	HotellingT^2	Exponential	M	Automotive
A32	Seif et al. (2011)		✓										ESD	HotellingT^2	Multivariate Normal	M	Automotive
A33	Faraz et al. (2012)		✓										ESD	HotellingT^2	Pivariate Normal	M	Automotive
A34	Lee et al. (2013)	✓											ED	TUKEY	Weibull	M	Electronic
A35	Mohammadian and Amiri (2013)	✓											ESD	Acceptance	Normal	M	Food
A36	Kuo and Chu (2013)											✓	RBD	$\bar{X}$	Binomial	M	Electronic

Continued on the next page

Table 6.5 continued from the previous page

ID	Ref.	Economic model										CD	CT	PD	AS	IA
		DCM	LVCM	BRCM	TLF	CRCM	KKCM	GWCM	BCM	ALF	CMM	UEM					
A37	Celano et al. (2014)				✓							✓	ED	Taguchi	Normal	M	Mechanical Parts
A38	Faraz et al. (2014)		✓										ESD	HotellingT^2	Pivariate Normal	M	Automotive
A39	Sitt et al. (2014)		✓										ESD	t	Normal	M	Food
A40	Seif et al. (2015)		✓										ESD	$\bar{X}$	Burr	M	Automotive
A41	Huang and Lu (2015)	✓			✓								ESD	EWMA	Normal	S	Health
A42	Amiri et al. (2015)		✓										ESD	EWMA	Normal	M	Tiles
A43	Kosztyan and Katona (2016)						✓						RBD	HotellingT^2	Normal	M	Automotive
A44	Tasias and Nenes (2016)											✓	ESD	$\bar{X}$, s	Normal	M	Chemical
A45	Park et al. (2017)											✓	ED	$\bar{X}$, EWMA, CUSUM	Normal	M	Chemical
A46	Tasias and Nenes (2017)											✓	ESD	$\bar{X}$, s	Normal	M	Aviation
A47	Zhou et al. (2017)		✓										ED	NP	Binomial	M	Undefined
A48	Rafie et al. (2017)			✓									ESD	HotellingT^2	Exponential	M	Undefined
A49	Nenes (2018)	✓											ESD	$\bar{X}$	Normal	M	Mechanical Parts
A50	Pedro et al. (2019)											✓	ESD	$\bar{X}$	Normal	M	Automotive
A51	Nadreri et al. (2019)											✓	ED	$\bar{X}$	Normal	M	Pulp and Paper
A52	Zheng et al. (2020)				✓								ED	$\bar{X}$	Weibull	M	Mechanical Parts
A53	Wang and Li (2020)			✓									ED	$\bar{X}$	Gamma	M	Food
A54	Shamsuzzaman et al. (2021)				✓								ESD	$\bar{X}$, EWMA	Normal	M	Chemical
A55	Naderi et al. (2021)											✓	ESD	$\bar{X}$	Weibull	M	Food
A56	Prata et al. (2021)											✓	RBD	$\bar{X}$	Normal	M	Food
A57	Attia and Abdel-Aal (2023)											✓	ED	NP	Binomial	M	Automotive
A58	Katona et al. (2023)						✓						RBD	$\bar{X}$, EWMA, CUSUM, MA	Normal	M	Automotive
A59	Saadatmellia et al. (2023)			✓									ED	$\bar{X}$	Burr	M	Chemical
A60	Haridy et al. (2023)	✓											ESD	NP	Normal and Rayleigh	M	Mechanical Parts
A61	Tavakoli and Heydari (2023)					✓							ESD	t	Exponential	M	Mechanical Parts
A62	Pasha et al. (2023)			✓									ED	$\bar{X}$& HotellingT^2	Weibull	M	Pulp and Paper
A63	Salmasnia et al. (2024)											✓	ESD	cause-selecting	Weibull	M	Textile
A64	Jafarian-Namin et al. (2024)											✓	ESD	ARMA	Weibull	M	Food
A65	Kalisetti et al. (2024)											✓	ESD	$\bar{X}$	Normal	M	Glass Manufacturing
A66	Shojaee et al. (2024)		✓										ESD	NP	Poisson	M	Chemical
A67	Sandeep and Ranjan Mukhopadhyay (2024)											✓	ESD	p	Bernoulli	M	Mechanical Parts
A68	Shi et al. (2024)											✓	ED	$\bar{X}$	Weibull	S	Inventory Mgt
A69	Lee and Chou (2024)				✓								ESD	TUKEY	Log-Normal	M	Electronic
A70	Shojaee et al. (2024)		✓										ESD	HotellingT^2	Chi-square	M	Mechanical Parts
A71	Sandeep and Mukhopadhyay (2024)	✓											ED	$\bar{X}$	Normal	M	Mechanical Parts

Notes. A check mark indicates that the corresponding economic model is used in the study. **Ref.** = reference/author(s); **CD** = chart design; **CT** = control chart type; **PD** = probability distribution; **AS** = application sector; **IA** = industry/application area. Within AS, **M** = manufacturing and **S** = service.

DCM = Duncan Cost Model; **LVCM** = Lorezen-Vance Cost Model; **BRCM** = Banerjee and Rahim Cost Model; **TLF** = Taguchi's Loss Function; **CRCM** = Costa and Rahim Cost Model; **KKCM** = Kosztyan and Katona Cost Model; **GWCM** = Gordon and Weindling's Cost Model; **BCM** = Bai's Cost Model; **ALF** = Alexander's Loss Function; **CMM** = Cost Minimization Model; **UEM** = Unknown Economic Model.

The author's publication related to the topic

Bibliography

Abbas, Z., Abbas, N., Nazir, H. Z., and Riaz, M. (2024a). Parametric and nonparametric versions of adaptive cusum charts for monitoring the location of individual measurements. *Journal of Statistical Computation and Simulation*, 94(12):2618–2645.

Abbas, Z., Nazir, H. Z., Akhtar, N., Abid, M., and Riaz, M. (2022). Non-parametric progressive signed-rank control chart for monitoring the process location. *Journal of Statistical Computation and Simulation*, 92(12):2596–2622.

Abbas, Z., Nazir, H. Z., and Riaz, M. (2024b). A distribution-free adaptive cusum-sign chart for monitoring shifts in the location of unknown industrial process. *Statistics*, 58(4):961–982.

Abbasi, M., Nishat, R. I., Bond, C., Graham-Knight, J. B., Lasserre, P., Lucet, Y., and Najjaran, H. (2024). A review of ai and machine learning contribution in predictive business process management (process enhancement and process improvement approaches). *arXiv preprint arXiv:2407.11043*.

Abid, M., Sun, M., Shabbir, A., Bakr, M., and Abbas, T. (2024). An enhanced nonparametric quality control chart with application related to industrial process. *Scientific Reports*, 14(1):13561.

Adekeye, K. S., Adewara, J. A., Aako, O. L., and Olaomi, J. O. (2021). Performance of median absolute deviation and some alternatives to median absolute deviation control charts for skewed and heavily tailed process. *Quality and Reliability Engineering International*, 37(8):3431–3440.

Al-Fedaghi, S. and Makdessi, M. (2020). Modeling business process and events. In *Computer Science On-line Conference*, pages 366–379. Springer.

Alduais, F. S. and Khan, Z. (2023). Ewma control chart for rayleigh process with engineering applications. *IEEE Access*, 11:10196–10206.

Alevizakos, V., Chatterjee, K., and Koukouvinos, C. (2021). Nonparametric triple exponentially weighted moving average signed-rank control chart for monitoring shifts in the process location. *Quality and Reliability Engineering International*, 37(6):2622–2645.

Ali, S., Abbas, Z., Nazir, H. Z., Riaz, M., Zhang, X., and Li, Y. (2020). On designing nonparametric ewma sign chart under ranked set sampling scheme with application to industrial process. *Mathematics*, 8(9):1497.

Almusaed, A., Almssad, A., and Yitmen, I. (2025). Interpretation of research findings and in-

depth discussion. In *Practice of Research Methodology in Civil Engineering and Architecture: A Comprehensive Guide*, pages 679–722. Springer.

Amjad, A., Azam, F., Anwar, M. W., Butt, W. H., and Rashid, M. (2018a). Event-driven process chain for modeling and verification of business requirements–a systematic literature review. *Ieee Access*, 6:9027–9048.

Amjad, A., Azam, F., Anwar, M. W., Butt, W. H., Rashid, M., and Naeem, A. (2018b). Umlpace for modeling and verification of complex business requirements in event-driven process chain (epc). *IEEE Access*, 6:76198–76216.

Angelastro, S. and Ferilli, S. (2020). Process model modularization by subprocess discovery. In *2020 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.

Antony, J. and Taner, T. (2003). A conceptual framework for the effective implementation of statistical process control. *Business Process Management Journal*, 9(4):473–489.

Aslam, M., Khan, M., Anwar, S. M., and Zaman, B. (2022). A homogeneously weighted moving average control chart for monitoring time between events. *Quality and Reliability Engineering International*, 38(2):1013–1044.

Aslam, M., Raza, M. A., Sherwani, R. A. K., Farooq, M., Jeong, J. Y., and Jun, C.-H. (2021). A mixed control chart for monitoring failure times under accelerated hybrid censoring. *Journal of Applied Statistics*, 48(1):138–153.

Avila, D. T., dos Santos, R. I., Mendling, J., and Thom, L. H. (2021). A systematic literature review of process modeling guidelines and their empirical support. *Business Process Management Journal*, 27(1):1–23.

Aykroyd, R. G., Leiva, V., and Ruggeri, F. (2019). Recent developments of control charts, identification of big data sources and future trends of current research. *Technological Forecasting and Social Change*, 144:221–232.

Baas, J., Schotten, M., Plume, A., Côté, G., and Karimi, R. (2020). Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative science studies*, 1(1):377–386.

Banerjee, P. and Rahim, M. (1987). The economic design of control charts: a renewal theory approach. *Engineering Optimization*, 12(1):63–73.

Bazan, P. and Estevez, E. (2020). Social business process management: Assessing the state of the art and outlining a research agenda. *Business Process Management Journal*, 26(1):191–211.

Bi, H. H. (2022). Applying statistical process control to teaching quality assurance at higher education institutions. *Quality Management Journal*, 29(2):145–157.

Bisiotis, K., Psarakis, S., and Yannacopoulos, A. N. (2022). Control charts in financial applications: An overview. *Quality and Reliability Engineering International*, 38(3):1441–1462.

Caivano, D. (2005). Continuous software process improvement through statistical process control. In *Ninth European Conference on Software Maintenance and Reengineering*, pages 288–293. IEEE.

Capizzi, G. and Masarotto, G. (2018). Phase i distribution-free analysis with the r package dfphase1. In *Frontiers in Statistical Quality Control 12*, pages 3–19. Springer.

Castagliola, P. and Figueiredo, F. O. (2013). The median chart with estimated parameters. *European Journal of Industrial Engineering*, 7(5):594–614.

Castillo, E. D. and Montgomery, D. C. (1996). A general model for the optimal economic design of x-bar charts used to control short or long run processes. *IIE transactions*, 28(3):193–201.

Celano, G. (2011). On the constrained economic design of control charts: a literature review. *Production*, 21:223–234.

Celano, G., De Magalhães, M. S., Costa, A. F., and Fichera, S. (2011). A stochastic shift model for economically designed charts constrained by the process stage configuration. *International Journal of Production Economics*, 132(2):315–325.

Centobelli, P., Cerchione, R., and Esposito, E. (2018). Environmental sustainability and energy-efficient supply chain management: A review of research trends and proposed guidelines. *Energies*, 11(2):275.

Chaudhary, A. M., Sanaullah, A., Hanif, M., Almazah, M. M., Albasheir, N. A., and Al-Duais, F. S. (2023). Efficient monitoring of a parameter of non-normal process using a robust efficient control chart: A comparative study. *Mathematics*, 11(19):4157.

Chen, Y.-K. (2003). An evolutionary economic-statistical design for vsi x control charts under non-normality. *The International Journal of Advanced Manufacturing Technology*, 22:602–610.

Chen, Y.-S. and Yang, Y.-M. (2002). An extension of banerjee and rahim's model for economic design of moving average control chart for a continuous flow process. *European Journal of Operational Research*, 143(3):600–610.

Chen, Y.-S. and Yu, F.-J. (2003). Determination of optimal design parameters of moving average control charts. *The International Journal of Advanced Manufacturing Technology*, 21:397–402.

Cheng, L., Du, L., Liu, C., Hu, Y., Fang, F., and Ward, T. (2024). Multi-modal fusion for business process prediction in call center scenarios. *Information Fusion*, 108:102362.

Chew, E. K. and Gottschalk, P. (2012). *Knowledge Driven Service Innovation and Management: IT Strategies for Business Alignment and Value Creation: IT Strategies for Business Alignment and Value Creation*. IGI Global.

Chou, C.-Y., Chen, C.-H., and Liu, H.-R. (2000). Economic-statistical design of x¥ charts for non-normal data by considering quality loss. *Journal of Applied Statistics*, 27(8):939–951.

Chou, C.-Y., Li, M.-H., and Wang, P.-H. (2001). Economic statistical design of average control charts for monitoring a process under non-normality. *The International Journal of Advanced Manufacturing Technology*, 17:603–609.

Colin, J. and Vanhoucke, M. (2015). Developing a framework for statistical process control approaches in project management. *International Journal of Project Management*, 33(6):1289–1300.

Costa, A. and Fichera, S. (2021). Economic-statistical design of adaptive arma control chart for autocorrelated data. *JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION*, 91(3):623–647.

Crowder, S. v. (1987). A simple method for studying run–length distributions of exponentially weighted moving average charts. *Technometrics*, 29(4):401–407.

Dahari, S., Talib, M. A., and Ghapor, A. A. (2025). Robust control chart application in semiconductor manufacturing process. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 43(2):203–219.

Das, K. R. and Imon, A. (2016). A brief review of tests for normality. *American Journal of Theoretical and Applied Statistics*, 5(1):5–12.

Daudin, J.-J. (1992). Double sampling x charts. *Journal of quality technology*, 24(2):78–87.

Deming, S. N. (2016). Statistics in the laboratory: control charts, part 1. *AMERICAN LABORATORY*, 48(1):40–41.

Diba, K., Batoulis, K., Weidlich, M., and Weske, M. (2020). Extraction, correlation, and abstraction of event data for process mining. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 10(3):e1346.

Fahland, D., Ghidini, C., Becker, J., and Dumas, M. (2020). Business process management. *Lecture Notes in Computer Science*.

Faraz, A., Kazemzadeh, R., and Saniga, E. (2010). Economic and economic statistical design of t 2 control chart with two adaptive sample sizes. *Journal of Statistical Computation and Simulation*, 80(12):1299–1316.

Ferreira, D. R. and Vasilyev, E. (2015). Using logical decision trees to discover the cause of process delays from event logs. *Computers in Industry*, 70:194–207.

Fitrianto, A., Choon, L. M., and Muhamad, W. Z. A. W. (2023). Simulation study for parametric ewma and npwewpa-sr control charts against non-normality assumptions. *CAUCHY: Jurnal Matematika Murni dan Aplikasi*, 8(2):157–166.

Gandy, A. and Kvaløy, J. T. (2013). Guaranteed conditional performance of control charts via bootstrap methods. *Scandinavian Journal of Statistics*, 40(4):647–668.

Ganguly, A. and Patel, S. K. (2019). Fuzzy multi-objective economic-statistical design of x-bar control chart. *International Journal of Productivity and Quality Management*, 27(4):435–463.

Gapeev, P. V. and Stoev, Y. I. (2025). Quickest change-point detection problems for multidimensional wiener processes. *Methodology and Computing in Applied Probability*, 27(1):2.

Gibbons, J. D. and Chakraborti, S. (2025). Nonparametric statistical inference. In *International encyclopedia of statistical science*, pages 1737–1740. Springer.

Godina, R., Matias, J., and Azevedo, S. (2016). Quality improvement with statistical process control in the automotive industry. *International Journal of Industrial Engineering and Management*, 7(1):1.

Goecks, L. S., Habekost, A. F., Coruzzolo, A. M., and Sellitto, M. A. (2024). Industry 4.0 and smart systems in manufacturing: Guidelines for the implementation of a smart statistical process control. *Applied System Innovation*, 7(2):24.

Goedhart, R., Schoonhoven, M., and Does, R. J. (2017). Guaranteed in-control performance for the shewhart x and x control charts. *Journal of Quality Technology*, 49(2):155–171.

Gonzalez, M. O. and Perry, M. B. (2025). Estimating the time of scale change in modern process monitoring applications. *Quality Engineering*, pages 1–8.

Gorgs, K., Friedrich, H., Vogel, T., and Hemmje, M. L. (2026). Towards service-oriented knowledge-based process planning supporting service-based smart production environments. *Software*, 5(1):8.

Grigg, O. A. and Spiegelhalter, D. J. (2008). An empirical approximation to the null unbounded steady-state distribution of the cumulative sum statistic. *Technometrics*, 50(4):501–511.

Hajej, Z., Nyoungue, A. C., Abubakar, A. S., and Mohamed Ali, K. (2021). An integrated model of production, maintenance, and quality control with statistical process control chart of a supply chain. *Applied Sciences*, 11(9):4192.

Haq, A. and Khoo, M. B. (2020). Memory-type multivariate charts with fixed and variable sampling intervals for process mean when covariance matrix is unknown. *Quality and Reliability Engineering International*, 36(1):144–160.

Hawkins, D. M. and Olwell, D. H. (2012). *Cumulative sum charts and charting for quality improvement*. Springer Science & Business Media.

Ho, C. and Case, K. E. (1994). Economic design of control charts: a literature review for 1981–1991. *Journal of quality Technology*, 26(1):39–53.

Ho, L. L., de Medeiros, P. G., and Borges, W. (2007). An alternative model for on-line quality monitoring for variables. *International Journal of Production Economics*, 107(1):202–222.

Ho, L. L. and Trindade, A. L. G. (2009). Economic design of an x chart for short-run production. *International Journal of Production Economics*, 120(2):613–624.

Hu, X. and Sun, J. (2015). Synthetic x chart for ar (1) autocorrelated processes. In *The 27th Chinese Control and Decision Conference (2015 CCDC)*, pages 7–12. IEEE.

Idogawa, J., Bizarrias, F. S., and Câmara, R. (2023). Critical success factors for change management in business process management. *Business Process Management Journal*, 29(7):2009–2033.

Ikpotokin, O. and Ishiekwene, C. (2016). Permutation approach in obtaining control limits and interpretation of out of control signals in multivariate control charts. *International Journal of Statistics and Applications*, 6(6):408–415.

Ismail, M. N., Kallow, S. M., Ridah, M. J., Abu-AlShaeer, M., and Khlaponin, Y. (2024). Quantitative insights and challenges in big data from a statistical perspective. *Journal of Ecohumanism*, 3(5):290–307.

John, B. and Subhani, S. (2020). A modified control chart for monitoring non-normal characteristics. *International Journal of Productivity and Quality Management*, 29(3):309–328.

Jones-Farmer, L. A., Jordan, V., and Champ, C. W. (2009). Distribution-free phase i control charts for subgroup location. *Journal of Quality Technology*, 41(3):304–316.

Katona, A. I., Saghir, A., Hegedűs, C., and Kosztyán, Z. T. (2023). Design of risk-based univariate control charts with measurement uncertainty. *IEEE Access*.

Kaya, I., Ilbahar, E., Gündoğdu, F. K., Karaşan, A., Yazır, K., and Olgac, E. (2025). Design of attribute control charts under uncertainty with normality analyses: Impact of operator hesitancy during inspection processes in manufacturing industry with a real case application. *Applied Soft Computing*, 170:112625.

Khilare, S. (2025). Increasing the sensitivity of cumulative quantity control chart using runs rules. *Journal of Statistical Sciences and Computational Intelligence Volume*, 1(4):294–311.

Kim, J. and Lim, C. (2021). Customer complaints monitoring with customer review data analytics: An integrated method of sentiment and statistical process control analyses. *Advanced Engineering Informatics*, 49:101304.

Knoth, S., Tercero-Gómez, V. G., Khakifirooz, M., and Woodall, W. H. (2021). The impracticality of homogeneously weighted moving average and progressive mean control chart approaches. *Quality and Reliability Engineering International*, 37(8):3779–3794.

Koo, T.-Y. and Case, K. E. (1990). Economic design of x-bar control charts for use in monitoring continuous flow processes. *The International Journal of Production Research*, 28(11):2001–2011.

Kooli, I. and Limam, M. (2009). Bayesian np control charts with adaptive sample size for finite production runs. *Quality and Reliability Engineering International*, 25(4):439–448.

Kord Toudeshki, L., Seyyedi, M. A., and Salajegheh, A. (2022). A context-aware architecture for realizing business process adaptation strategies using fuzzy planning. *International Journal of Software Engineering and Knowledge Engineering*, 32(01):37–70.

Kosztyán, Z. T. and Katona, A. I. (2016). Risk-based multivariate control chart. *Expert Systems with Applications*, 62:250–262.

Kosztyán, Z. T. and Katona, A. I. (2018). Risk-based x-bar chart with variable sample size and sampling interval. *Computers & Industrial Engineering*, 120:308–319.

Kosztyán, Z. T., MacClever, A., Khan, Z., Hegedűs, C., Saghir, A., Csizmadia, T., and Katona, A. I. (2026). Advancing process monitoring: A distribution-free control framework for operation processes. *Computers in Industry*, 177:104449.

Koutras, M. V. and Triantafyllou, I. S. (2018). A general class of nonparametric control charts. *Quality and Reliability Engineering International*, 34(3):427–435.

Li, J. (2021). Application of statistical process control in engineering quality management. In *IOP Conference Series: Earth and Environmental Science*, volume 831, page 012073. IOP Publishing.

Li, W. and Qiu, P. (2020). A general charting scheme for monitoring serially correlated data with short-memory dependence and nonparametric distributions. *IISE Transactions*, 52(1):61–74.

Liu, L., Peng, Q., Lai, X., and Deng, Z. (2021). An adaptive nonparametric exponentially weighted moving average control chart with dynamic sampling intervals. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 14(1):74–87.

Lizarelli, F. L., Bessi, N. C., Oprime, P. C., Amaral, R. M. d., and Chakraborti, S. (2016). A bibliometric analysis of 50 years of worldwide research on statistical process control. *Gestão & Produção*, 23(04):853–870.

Lofthouse, T. (1999). The taguchi loss function. *Work Study*, 48(6):218–223.

Lu, C.-W. and Reynolds Jr, M. R. (2001). Cusum charts for monitoring an autocorrelated process. *Journal of Quality Technology*, 33(3):316–334.

Lu, S.-L., Chen, M.-C., Chen, J.-H., Yang, S.-F., and Chatterjee, K. (2025). Considering aewma control chart applied to gamma-distributed data with fixed and variable sampling intervals. *Scientific Reports*.

Mahmood, T., Hyder, M., and Raza, S. M. M. (2025). Improved ewma and cusum charts under modified successive sampling for monitoring process dispersion. *Journal of Statistical Theory and Applications*, 24(2):436–468.

Mason, B. and Antony, J. (2000). Statistical process control: an essential ingredient for improving service and manufacuring quality. *Managing Service Quality: An International Journal*, 10(4):233–238.

Minguez, J., Zor, S., and Reimann, P. (2011). Event-driven business process management in engineer-to-order supply chains. In *Proceedings of the 2011 15th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 624–631. IEEE.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., Group, P., et al. (2010). Preferred reporting items for systematic reviews and meta-analyses: the prisma statement. *International journal of surgery*, 8(5):336–341.

Montgomery, D. C. (2020). *Introduction to statistical quality control*. John wiley & sons.

Mukherjee, A. and Chakraborti, S. (2012). A distribution-free control chart for the joint monitoring of location and scale. *Quality and Reliability Engineering International*, 28(3):335–352.

Mundwiller, S. (2017). *Statistical process control: A pragmatic approach*. CRC Press.

Muñoz, J. J., Aslam, M., and Campuzano, M. J. (2023). Optimized repetitive sampling x-bar control chart: performance evaluation and comparison with shewhart control chart. *Frontiers in Applied Mathematics and Statistics*, 9:1285023.

Muralidharan, N., Johnson, T., Rose, L. S., and Davis, M. (2024). Cpv monitoring-optimization of control chart design by reducing the false alarm rate and nuisance signal. *Science Journal of Applied Mathematics and Statistics*, 12(2):20–28.

Myles, A. J., Feudale, R. N., Liu, Y., Woody, N. A., and Brown, S. D. (2004). An introduction to decision tree modeling. *Journal of Chemometrics: A Journal of the Chemometrics Society*, 18(6):275–285.

Nadreri, M. H., Bameni Moghadam, M., and Seif, A. (2019). Statistically constrained economic design of x control chart with weibull in-control time for processes subject to multiple assignable causes. *International Journal of Quality & Reliability Management*, 36(4):526–551.

Nafisah, I. A., Almazah, M. M., Al-Rezami, A., and Hussain, S. (2025). Variable sample size based ewma control chart with an exponential scaling mechanism for production process monitoring. *Scientific Reports*, 15(1):30964.

Niaki, S. T. A., Gazaneh, F. M., and Toosheghanian, M. (2014). A parameter-tuned genetic algorithm for economic-statistical design of variable sampling interval x-bar control charts for non-normal correlated samples. *Communications in Statistics-Simulation and Computation*, 43(5):1212–1240.

Nimbale, S. and Ghute, V. (2021). Neural network based non-parametric control chart for location. *International Journal of Statistics and Reliability Engineering*, 8(3):381–387.

Odhiambo, J., Weke, P., and Wendo, J. (2020). Modeling of returns of nairobi securities exchange 20 share index using log-normal distribution. *Research Journal of Finance and Accounting*, 11(8):77–82.

Oladipupo, O. O., Adekeye, K. S., Olaomi, J. O., and Alayande, S. A. (2025). Improved non-parametric double homogenously weighted moving average control chart for monitoring changes in process location. *Statistics, Optimization & Information Computing*, 14(5):2118–2130.

Peerajit, W. (2020). An approximation to the average run length on a cusum control chart with a numerical integral equation method for a long-memory arfimax model. *Journal of Applied Science and Emerging Technology*, 19(2):37–51.

Peres, F. A. P. and Fogliatto, F. S. (2018). Variable selection methods in multivariate statistical process control: A systematic literature review. *Computers & Industrial Engineering*, 115:603–619.

Petkov, N. and Ivanova, M. (2024). Printed circuit board and printed circuit board assembly methods for testing and visual inspection: a review. *Bulletin of Electrical Engineering and Informatics*, 13(4):2566–2585.

Prajapati, D. (2010). Effect of sampling intervals on economic design of proposed x-bar chart using lorenzen-vance cost model. *International Journal of Productivity and Quality Management*, 6(4):518–539.

Prasetyaji, M. R., Puspita, N. F., and Taufik, T. A. (2025). Improvement of project monitoring model using a combination of quality function deployment and lean six sigma at pt tec. *Eduvest-Journal of Universal Studies*, 5(6):6080–6097.

Qiu, P. and Hawkins, D. (2001). A rank-based multivariate cusum procedure. *Technometrics*, 43(2):120–132.

Rashid, K. M. J. (2022). Construction skewness correction the and r control chart under non–normality. *Zanco Journal of Human Sciences*, 26(1):237–246.

Raza, M., Aslam, N., Le-Minh, H., Hussain, S., Cao, Y., and Khan, N. M. (2017). A critical analysis of research potential, challenges, and future directives in industrial wireless sensor networks. *IEEE Communications Surveys & Tutorials*, 20(1):39–95.

Raza, M. A., Tariq, F., Zaagan, A. A., Engmann, G. M., Mahnashi, A. M., and Meetei, M. Z. (2024). A nonparametric mixed exponentially weighted moving average-moving average control chart with an application to gas turbines. *Plos one*, 19(8):e0307559.

Riaz, M., Alshammari, H., Abbas, N., and Mahmood, T. (2025). Navigating process drift:

The power of cusum in monitoring air quality processes and maintenance operations. *Arabian Journal for Science and Engineering*, 50(14):11145–11166.

Sabahno, H. (2023). An adaptive max-type multivariate control chart by considering measurement errors and autocorrelation. *JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION*, 93(16):2956–2981.

Saeed, N., Bataineh, A. M. F., Abu-Shawiesh, M. O. A., and Haddad, F. (2024). Sensitivity and reliability comparisons of ewma mean control chart based on robust scale estimators under non-normal process: Covid data application. *Quality and Reliability Engineering International*, 40(8):4513–4529.

Saesuntia, P., Areepong, Y., and Sukparungsee, S. (2025). A robust tewma–ma control chart based on sign statistics for effective monitoring of manufacturing processes. *Mathematics*, 13(23):3789.

Sałaciński, T., Chrzanowski, J., and Chmielewski, T. (2023). Statistical process control using control charts with variable parameters. *Processes*, 11(9):2744.

Saleh, N. A., Aly, A. A., and Mahmoud, M. A. (2024). Effect of contaminated phase i data on the phase ii–ewma control chart performance under non-normality. *Communications in Statistics-Simulation and Computation*, 53(9):4430–4448.

Sauers, D. G. (1999). Using the taguchi loss function to reduce common-cause variation. *Quality Engineering*, 12(2):245–252.

Severin, T. and Schmid, W. (1998). Statistical process control and its application in finance. In *Risk Measurement, Econometrics and Neural Networks: Selected Articles of the 6th Econometric-Workshop in Karlsruhe, Germany*, pages 83–104. Springer.

Shah, M. T., Azam, M., Aslam, M., and Sherazi, U. (2021). Time between events control charts for gamma distribution. *Quality and Reliability Engineering International*, 37(2):785–803.

Sheu, S.-H. and Yang, L. (2006). The generally weighted moving average control chart for monitoring the process median. *Quality Engineering*, 18(3):333–344.

Siegmund, D. (2013). *Sequential analysis: tests and confidence intervals*. Springer Science & Business Media.

Sofikitou, E. M. and Koutras, M. V. (2020). Multivariate nonparametric control charts based on ordered samples, signs and ranks. In *Distribution-free methods for statistical process monitoring and control*, pages 57–105. Springer.

Song, W., Chen, D., and Zio, E. (2023). Heavy tail and long-range dependence for skewed time series prediction based on a fractional weibull process. *Fractal and Fractional*, 8(1):7.

Stary, C. (2014). Non-disruptive knowledge and business processing in knowledge life cycles–aligning value network analysis to process management. *Journal of Knowledge Management*, 18(4):651–686.

Tapang, W., Pongpullponsak, A., and Sarikavanij, S. (2016). Three non-parametric control charts based on ranked set sampling. *Chiang Mai Journal of Science*, 43(4):914–929.

Teoh, J. W., TEOH, W., CHONG, Z., Lee, M. H., and Khaw, K. W. (2024). A robust design

for the omnibus sprt control chart under skewed data distributions. *Sains Malaysiana*, 53(6):1441–1461.

Teoh, W. L., Le Goh, K., Chong, Z. L., Chew, X., Lee, M. H., and Khaw, K. W. (2025). Optimising variable sample size x-bar chart through median run length with estimated process parameters. *Sains Malaysiana*, 54(4):1187–1207.

Thor, J., Lundberg, J., Ask, J., Olsson, J., Carli, C., Härenstam, K. P., and Brommels, M. (2007). Application of statistical process control in healthcare improvement: systematic review. *BMJ Quality & Safety*, 16(5):387–399.

Toledo, J. C. d., Lizarelli, F. L., and Santana, M. B. (2017). Success factors in the implementation of statistical process control: action research in a chemical plant. *Production*, 27:e20162208.

Torng, C., Lee, P.-H., Liao, H.-S., and Liao, N.-Y. (2009). An economic design of double sampling x charts for correlated data using genetic algorithms. *Expert Syst. Appl.*, 36:12621–12626.

Ueda, R. M., Agostino, Ì. R., and Souza, A. M. (2022). Analysis and perspectives on multivariate statistical process control charts used in the industrial sector: a systematic literature review. *Management and Production Engineering Review*, 13.

Van der Aalst, W. M. (1999). Formalization and verification of event-driven process chains. *Information and Software technology*, 41(10):639–650.

van der Aalst, W. M., Reijers, H. A., and Maruster, L. (2024). Process mining beyond workflows. *Computers in Industry*, 161:104126.

Votto, R., Lee Ho, L., and 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.

Wagner, G. (2021). Business process modeling and simulation with dpmn: processing activities. In *2021 Winter Simulation Conference (WSC)*, pages 1–15. IEEE.

Wang, C.-H. and Li, F.-C. (2020). Economic design under gamma shock model of the control chart for sustainable operations. *Annals of Operations Research*, 290(1-2):169–190.

Xie, M., Goh, T. N., and Kuralmani, V. (2002). *Statistical models and control charts for high-quality processes*. Springer Science & Business Media.

Xie, X. and Qiu, P. (2023). Control charts for dynamic process monitoring with an application to air pollution surveillance. *The Annals of Applied Statistics*, 17(1):47–66.

Xue, L. and Qiu, P. (2021). A nonparametric cusum chart for monitoring multivariate serially correlated processes. *Journal of Quality Technology*, 53(4):396–409.

Yang, S. and Rahim, M. (2005). Economic statistical process control for multivariate quality characteristics under weibull shock model. *International Journal of Production Economics*, 98(2):215–226.

Yang, S.-F. (2005). Dependent processes control for overadjusted process means. *The International Journal of Advanced Manufacturing Technology*, 26:109–116.

Yao, Y., Chakraborti, S., Yang, X., Parton, J., Lewis, D., and Hudnall, M. (2023). Phase i control chart for individual autocorrelated data: application to prescription opioid monitoring. *JOURNAL OF QUALITY TECHNOLOGY*, 55(3):302–317.

You, H., Chong, Z., Teoh, W. L., Khoo, M., and Yeong, W. (2023). An expected average run length (earl) performance comparison of the ssgr and ewma control charts. *International Journal of Integrated Engineering*, 15(5):35–40.

Zaka, A., Jabeen, R., and Khan, K. I. (2021). Control charts for the shape parameter of skewed distribution. *Intelligent Automation & Soft Computing*, 30(3):1007–1018.

Zasadzień, M. and Midor, K. (2018). Statistical process control as a failure removal improvement tool. *Acta technologica agriculturae*, 21(3):124–129.

Zwetsloot, I. M., Jones-Farmer, L. A., and Woodall, W. H. (2024). Monitoring univariate processes using control charts: Some practical issues and advice. *Quality Engineering*, 36(3):487–499.