Enhancing container terminal performance through an integrated SPC-DMAIC methodology: an empirical case study

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Abstract

Purpose – This paper examines how Statistical Process Control (SPC) can support the monitoring and control of container ship loading and unloading operations by embedding multivariate process monitoring within the Define Measure Analyse Improve Control (DMAIC) improvement framework. This paper aims to demonstrate how established SPC principles can be coherently operationalised to address unproductive time in complex port service environments.

Design/methodology/approach – The study adopts a single-case research design based on operational data collected from a major Spanish container terminal. A multivariate Hotelling's T^2 control chart is applied during Phase I analysis to jointly monitor vessel turnaround time, number of containers handled and crane movements. These SPC tools are systematically integrated within the DMAIC cycle to structure problem definition, measurement, analysis and improvement planning in a real operational setting.

Findings – The results show that multivariate SPC, when integrated within DMAIC, offers enhanced diagnostic insight compared with univariate monitoring by capturing the joint behaviour of interdependent operational variables. The Phase I analysis reveals statistically identifiable sources of variability that align with documented operational disruptions and planning deficiencies, thereby supporting more informed root cause analysis and prioritisation of improvement actions. The findings illustrate the feasibility and practical value of the proposed approach, while remaining confined to exploratory, single-case evidence.

Practical implications – The framework provides actionable guidance for port managers seeking to enhance process visibility, detect operational instability and support data-driven continuous improvement. By linking multivariate SPC signals to DMAIC-based decision processes, the study offers a structured approach for managing variability in vessel service operations under real-world constraints.

Originality/value – This study contributes to the Lean Six Sigma (LSS) literature by integratively adapting and operationalising established SPC and DMAIC principles within a complex maritime service context. The paper demonstrates how multivariate SPC can be coherently embedded within DMAIC to support process monitoring in container terminal operations.

Keywords Port terminal, Vessel turnaround time, Quality of Service, Statistical Process Control, Lean Six Sigma

Paper type Case report

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1. Introduction

International shipping accounts for approximately 80% of global trade, with even higher shares in developing countries (UNCTAD, 2024). Ports, as the backbone of intermodal freight systems, play a critical role in sustaining this flow (Sheikholeslami *et al.*, 2013). The rapid growth of containerised trade has intensified competition among terminals, making the improvement of Quality of Service (QoS) a strategic priority for port survival (Kaliszewski *et al.*, 2020). QoS in seaports directly influences global supply chains and economic development, which explains the increasing academic and practical interest in optimising port operations (Bierwirth and Meisel, 2010, 2015; Carlo *et al.*, 2014, 2015; Covic, 2018; Le *et al.*, 2020; Lehnfeld and Knust, 2014; Mwendapole and Jin, 2021; Nguyen *et al.*, 2022; Rahman *et al.*, 2023; Sakyi, 2020; Zhen, 2013).

Vessel turnaround time is widely recognised as a critical indicator of port efficiency, as prolonged docking periods reduce berth availability and increase operational costs for shipping lines (Ansorena, 2018; Kizilay and Eliiyi, 2021). Consequently, minimising turnaround time is essential to enhance service quality and maintain competitiveness. Despite its importance, delays persist because of structural and procedural inefficiencies, including rigid authorisation protocols, inadequate infrastructure, poor communication among stakeholders, workforce shortages and limited interoperability (Moszyk *et al.*, 2021; Almeida, 2023; Nikghadam *et al.*, 2023).

These constraints often lead to unproductive time during a vessel's stay at the terminal, undermining operational effectiveness. Operational bottlenecks along the quay are primarily rooted in planning and coordination gaps at the berth–crane interface and in information frictions across port-community actors. Empirical and review evidence shows that suboptimal berth allocation and quay crane assignment/scheduling systematically extend service times and vessel turnaround, particularly under uncertainty and maintenance contingencies (Makhado *et al.*, 2025; Li and Song, 2025). Manual or fragmented documentation across agents, customs and terminal systems extends the duration of port calls. Port-community digitalisation, including electronic bills of landing and common messaging standards, reduces delays (Rodrigue *et al.*, 2026). In addition, resource-allocation mismatches between workforce availability, quay windows and landside capacity propagate queues and under-utilisation; key operational KPIs – gross crane rate, ship working hours and truck/rail turn-times – explain a substantial share of variation in ship turnaround time (Mazibuko *et al.*, 2024).

From the port's perspective, reducing docking time not only improves berth utilisation but also strengthens dynamic capacity to accommodate additional services (Kizilay and Eliiyi, 2021; Ansorena, 2018). Overcoming these challenges requires the deployment of systematic, data-driven performance-control mechanisms, including real-time monitoring dashboards, standardised process metrics and continuous-improvement routines aligned with Lean Six Sigma (LSS) methodologies to ensure responsiveness to growing demands for speed and cost efficiency.

Over the past two decades, LSS has become a key methodology for process management due to its effectiveness in reducing waste, improving quality, and limiting variability. (Antony *et al.*, 2017). Lean primarily targets the elimination of non-value-added activities, whereas Six Sigma focuses on controlling variation and driving quality improvements through data-based decision-making (Ichsan *et al.*, 2020; Gomaa, 2025). Their integration as LSS combines the speed of Lean with the precision of Six Sigma, offering a powerful approach to simultaneous efficiency and quality enhancement (Kurnia and Purba, 2021).

LSS adopts the Define Measure Analyse Improve Control (DMAIC) cycle as its principal methodology for improvement initiatives, combining Lean tools across all phases with statistical techniques to enhance process reliability. Therefore, DMAIC offers a disciplined, data-driven approach that supports problem-solving, variation reduction and sustained continuous improvement (Mogatusi *et al.*, 2025; Wartati *et al.*, 2021).

Although LSS has achieved substantial success in manufacturing and service industries, its application within maritime operations remains scarce and dispersed (Egbumokei *et al.*, 2024; Neves *et al.*, 2024, 2025; Roby and Iswanto, 2024). Specific aspects of port processes, such as extended cycle times, complex supply chains and high operational costs, position ports as an especially relevant context for the implementation of LSS (Hia, 2025).

Among LSS, Statistical Process Control (SPC) is regarded as one of the most powerful tools for ensuring process stability and driving continuous improvement (Ichsan *et al.*, 2020; Gomaa, 2025). Even though SPC is widely recognised for process improvement, its use in seaport operations is limited and predominantly univariate, relying on charts such as $\bar{X}$-R for single indicators. Multivariate approaches are virtually absent.

To address this gap, we propose an integrative, context-specific framework that systematically embeds multivariate SPC within the DMAIC improvement cycle for monitoring and diagnosing process stability in container terminal operations. The main contribution lies in the monitoring and diagnostic architecture and its operationalisation in a complex maritime service setting, showing how this integration enables the detection and interpretation of multivariate process instability with traceability to support decision-making.

Accordingly, this study addresses the following research question: How does SPC support the monitoring and control of container ship loading and unloading operations through the DMAIC framework? To address the research question, SPC principles are combined with the LSS DMAIC methodology to develop a multivariate monitoring approach. This integration enhances process control and supports data-driven decision-making for continuous improvement in port operations.

This study adopts a single-case design to implement and evaluate SPC within a port terminal. As Yin (2017) emphasises, single-case studies enable an in-depth examination of complex settings – such as container loading and unloading – by capturing rich qualitative and quantitative data on processes, resources and regulations. The selected terminal offers a particularly insightful context: it is strategically located, handles high traffic volumes and allows frequent researcher access, facilitating comprehensive data collection and field observations. These conditions provide a unique opportunity to analyse operational dynamics under real-world constraints and validate the proposed SPC-based framework.

Furthermore, the case study approach is especially suitable for exploratory research, as it supports the identification of relevant factors, key variables and emerging themes that can guide subsequent quantitative investigations (Ketokivi and Choi, 2014). Its capacity to enable direct observation and data collection in natural operational environments aligns with established patterns in maritime research, where empirical, field-based studies dominate because of the process-oriented nature of LSS and its reliance on tangible operational evidence. This trend highlights both the practical relevance of case-based inquiry in ports, shipyards and maritime supply chains and the ongoing need for broader integrative and perception-driven studies in the sector (Hia, 2025).

Beyond its methodological contribution, this research provides port managers with practical guidance to address operational inefficiencies and enhance QoS. It shows that LSS methodologies, although rooted in manufacturing, can effectively alleviate process constraints in port services. As a result, these process improvements also lead to additional progress towards the Sustainable Development Goals (SDGs) (UNCTAD, 2022).

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature; Section 3 details the research methodology; Sections 4 and 5 present and discuss the results; and Section 6 concludes with limitations and future research directions.

2. Literature review

2.1 Total quality management, Lean Six Sigma and port services

Total Quality Management (TQM) is a managerial approach to long term success through customer satisfaction that promotes cost reduction, the delivery of high-quality goods and services, employee empowerment and outcome measurement (Gunasekaran and McGaughey, 2003).

In this context, Six Sigma – a methodology introduced by Motorola in the 1980s that significantly enhanced business quality – has been increasingly adopted across the business environment, regardless of the type or characteristics of the companies. This methodology focuses on improving quality by reducing errors and variation. Considering a defect as any event in which a product or service fails to meet the customer's requirements, the goal of Six Sigma is to reach a maximum of 3.4 Defects per Million Opportunities (DPMO) (Crosby, 1979; Harry and Schroeder, 2006).

To improve existing process problems and enhance the quality of results, Six Sigma follows the DMAIC approach, while the Define–Measure–Analyse–Design–Verify approach is used for projects focused on the creation of a new product or process design. Six Sigma is a data-driven method that uses a wide variety of statistical tools, such as SPC, regression, Design of Experiments and Failure Mode and Effects Analysis (FMEA), as well as management tools, such as Suppliers–Inputs–Process–Outputs–Customers (SIPOC), Critical to Quality trees or the Voice of the Customer (Hahn *et al.*, 1999, 2000; Kwak and Anbari, 2006; Montgomery and Woodall, 2008; Ung and Chen, 2010).

Alongside Six Sigma, Lean has emerged as one of the most influential management approaches for enhancing operational performance, thanks to its emphasis on eliminating non-value-added activities and streamlining process flows (Ichsan *et al.*, 2020; Gomaa, 2025). When combined with Six Sigma's analytical orientation, Lean adds speed and waste-reduction capabilities, resulting in the highly effective integrated improvement methodology known as LSS (Kurnia and Purba, 2021). The integration of LSS is generally operationalised through the DMAIC framework, providing a structured roadmap for the identification, diagnosis and resolution of performance issues (Trubetskaya *et al.*, 2023).

LSS was initially adopted within the manufacturing industry, where it proved highly effective in reducing costs, minimising defects, eliminating waste, shortening production cycles and improving customer satisfaction (de Freitas and Costa, 2017; Duc and Thu, 2022). Its demonstrated ability to enhance value delivery and profitability led to a progressive expansion beyond manufacturing into diverse service sectors, including finance, education, health care, government, software and construction, as well as broader industries such as agriculture, oil and gas (Adeodu *et al.*, 2021; Archana and Kumar, 2024; Atanas *et al.*, 2016; Gupta *et al.*, 2020; Snee, 2004; Sony and Naik, 2020; Zolkepley *et al.*, 2018; Widjajanto and Hardi Purba, 2021).

Within the service sector, port operations represent a critical area for LSS application, owing to their central role in global trade and economic development. Ports enable the movement of goods and services across multimodal corridors that integrate maritime, road and rail infrastructures (Ridwan and Noche, 2018). Their operational efficiency directly influences competitiveness, environmental sustainability and social equity, positioning ports as key actors in achieving the SDGs (UNCTAD, 2022). In maritime operations, Lean targets non-value-added activities, while Six Sigma focuses on variation control and data-driven quality improvement (Ichsan *et al.*, 2020; Gomaa, 2025). Their integration as LSS combines efficiency with precision, offering a robust approach to operational excellence (Kurnia and Purba, 2021). Consequently, adopting LSS principles in port operations is not merely advantageous but essential, serving as a strategic differentiator in an increasingly competitive logistics environment (Marlow and Paixao-Casaca, 2003).

To frame the theoretical foundations of LSS in port operations, Table 1 summarises the studies we judge most relevant for clarifying what has been investigated to date, what remains to be addressed and, consequently, the contribution of our paper (last column). To do so in a systematic and transparent manner, we identified four variables that allow us to highlight the specific value added by our study when contrasted with the existing literature. These variables are as follows:

(1) controlled process;

(2) quality characteristic analysed;

(3) application of Multivariable SPC (MSPC); and

(4) application of the DMAIC approach.

Using these dimensions, we indicate concretely what our study accomplishes relative to each prior study.

The LSS literature on port services and operations reveals, first, an operational stream focused on terminal and gate improvements, where DMAIC and classical tools – SIPOC, Ishikawa, benchmarking and multi-voting – are used to cut guaranteed time overruns and delays, supported by organisational redesign and enabling technologies (Moszyk and Deja, 2023). Following the deployment of optical character recognition (OCR) technologies, control charts and Ishikawa diagrams have been used to analyse new gate transaction times, identify statistical instabilities and trace causes to guide corrective actions (Kusnoaji and Ratih, 2021). Similarly, service time at gate out has been assessed with control charts and Ishikawa to standardise service and tighten variability (Putra and Ratih, 2021).

A second line of inquiry develops system-level frameworks and performance metrics. Ridwan and Noche (2018) integrate Six Sigma with system dynamics to simulate handling flows and use indicators – sigma value, process capability indices and cost of poor quality – to remove waste. To tackle truck congestion, Nooramin *et al.* (2011) propose a Six Sigma framework combining DMAIC and FMEA to reduce queues and turnaround times at landside gates. In parallel, SPC has been applied to maritime inspections via X–R control charts to detect anomalous periods and manage variability (Yuan *et al.*, 2020).

A third stream addresses energy and environmental performance monitoring of vessels. At voyage level, Capezza *et al.* (2019, 2020) provide a statistical framework (PLS regression) and an automatic reporting system for fuel consumption (and thus CO_2 emissions) monitoring. Vessel arrival monitoring has also been approached with deep learning models combined with control charts (El Mekkaoui *et al.*, 2024).

Recent work advances digitalised improvement through integrated DMAIC technology approaches (DMAIC 4.0). In dry bulk ports, Sirajuddin *et al.* (2025) develop and operationalise an adaptive DMAIC 4.0 approach for loading/unloading, leveraging IoT-based real-time monitoring, predictive analytics and process automation as decision support and control enablers. In parallel, an AI-centred, real-time surveillance line is emerging: monitoring statistics based on variational autoencoders (VAE) are compared and integrated with cumulative sum (CUSUM) for automatic identification system (AIS) data (Oh *et al.*, 2025), and convolutional neural network (CNN)–long short-term memory (LSTM) models are used for real-time detection of anomalous vessel behaviours (Qi *et al.*, 2025).

Table 1. Review of LSS applications in port operations and related services

Authors	Objective	Tools	Geographic scope	Contribution* 1	2	3	4
El Mekkaoui *et al.* (2024)	To develop a methodology to monitor the vessel arrival process	Deep learning sequence models and SPC	Morocco	√	√	√	√
Kusnoaji and Ratih (2021)	To analyse time motion transactions to enhance the quality of container export/import services after the implementation of optical character recognition technologies	Analysis of capability, $\bar{x}$-S chart, Ishikawa diagram	Indonesia			√	√
Putra and Ratih (2021)	To determine the performance of gate operators through the measurement of the time they spend to accomplish their duties	$\bar{x}$-R chart, Ishikawa diagram	Indonesia	√	√	√	√
Dewi and Ratih (2021)	To control the quality of container problems that enter the exception area by determining the average time to resolve container problems	LSS, U-Chart, Ishikawa diagram	Indonesia	√	√	√	√
Yuan *et al.* (2020)	To explore the application of SPC on Maritime inspections	$\bar{x}$-R chart, cause-and-effect diagram	Taiwan	√	√	√	√
Capezza *et al.* (2020)	To propose a novel procedure to continuously monitor operating conditions and total CO_2 emissions at each voyage of a cruise ship	Functional data analysis, multivariate functional principal component analysis, profile monitoring, statistical process monitoring	Italy	√	√	√	√
Ramadhan *et al.* (2020)	To assess whether the quality of the output of the agent-based simulation of ship, truck and crane operation remains consistent	$\bar{x}$-R chart	Indonesia	√	√	√	√
Capezza *et al.* (2019)	To provide a statistical framework and automatic reporting system for fuel consumption (and thus CO_2 emissions) monitoring	Partial Least Squares (PLS); Hotelling's T^2 chart, SPE_x control charts	Italy	√	√		√

(*continued*)

Table 1. Continued

Authors	Objective	Tools	Geographic scope	Contribution* 1	2	3	4
Ansorena (2018)	To propose a method based on SPC to measure and analyse the time spend by container ships at port	Exponentially weighted moving average (EWMA) chart	Spain			√	√
Ridwan and Noche (2018)	To develop a comprehensive model for port performance metrics to enhance port quality by integrating the Six sigma methodology with a system dynamics approach	Sigma value, process capability indices, cost of poor quality	Indonesia		√	√	√
Nooramin *et al.* (2011)	To use an optimization model to minimize trucks' congestion and their turn-around times	Optimization model/ I-MR chart/ cause and effect diagram/ FMEA analysis	Iran	√	√	√	√
Ung and Chen (2010)	To examine the current quality level of the cargo handling performance in a container terminal	DMAIC, $\bar{x}$-R chart/ Ishikawa diagram	Taiwan			√	
Sirajuddin *et al.* (2025)	To develop and operationalize an adaptive DMAIC-4.0 approach for dry-bulk loading and unloading operations	DMAIC, Six sigma tools (fishbone diagram, pareto and FMEA Analysis), technology 4.0	Indonesia			√	
Moszyk and Deja (2023)	To identify strategies that minimize average overruns of guaranteed service time for trucks carrying import/ export/ transit containers	DMAIC, SIPOC, pareto diagram, scatterplot, benchmark, brainstorming and multi-voting tool	Poland	√	√	√	
Praharsi *et al.* (2021)	To enhance continuous improvement and resilience in the maritime industry during COVID-19	DMAIC, brainstorming, DPMO, sigma value, fishbone diagram, FMEA analysis	Indonesia		√	√	
Gonzalez *et al.* (2025)	To show how lean tools and TQM methodologies improve efficiency and competitiveness in port operations (benchmarking)	Fishbone diagram, value stream mapping (VSM), overall equipment effectiveness (OEE), DMAIC, bottleneck analysis, Kanban, 5S, quality function deployment	USA, Costa Rica and Spain	√	√	√	√

(continued)

Table 1. Continued

Authors	Objective	Tools	Geographic scope	Contribution* 1	2	3	4
Oh *et al.* (2025)	To develop an advanced real-time surveillance methodology that integrates variational autoencoders (VAE)-based statistical indicators with a cumulative sum (CUSUM) chart for the continuous monitoring of automatic identification system (AIS) data	VAE-based monitoring statistics with the CUSUM chart	Korea	√	√	√	√
Qi *et al.* (2025)	To propose a method for real-time detection of vessel abnormal behaviour based on convolutional neural network (CNN) and long short-term memory (LSTM)	EWMA method to filter out noise in real-time data (longitude/ latitude/ speed/course)	China	√	√	√	√
Gomaa (2026)	To optimize supply chain management by reducing waste and improving process performance	LSS-DMAIC framework: Pareto chart, control charts, fishbone analysis, process capability analysis, value stream mapping	Egypt	√	√	√	
Hajji *et al.* (2025)	To improve administrative efficiency, reduce delays and enhance service quality in a public transportation	LSS-DMAIC framework: Measurement system analysis, $\bar{x}$-R chart, capability analysis	Tunisia	√	√	√	
Al-Qatawneh *et al.* (2025)	To reduce the baggage-handling process in the arrivals area of an international airport	Six sigma–DMAIC approach, cause and effect diagram, I_MR chart, process capability	Middle east region	√	√	√	

Note(s): *1: does not focus on the container loading/unloading process, 2: does not focus on turnaround time, 3: does not apply MSPC, 4: does not apply DMAIC approach
Source(s): Authors' own work

At the organisational and sectoral levels, prior work shows that integrating LSS with supply chain resilience capabilities helped maritime organisations sustain performance during COVID-19 (Praharsi *et al.*, 2021); that benchmarking of lean and TQM practices delivers strategic roadmaps to lift port efficiency and competitiveness (Gonzalez *et al.*, 2025); and that stakeholder based evidence links waste elimination, continuous improvement and shorter cycle times to superior logistics performance (Mwambipile and Ryoba, 2025).

Finally, although outside the strict port domain, the transferability of LSS to related services is noteworthy: DMAIC frameworks for administrative processes in public transport (Hajji *et al.*, 2025), DMAIC applications to airport baggage handling (Al Qatawneh *et al.*, 2025) and an LSS + DMAIC supply chain framework in manufacturing reporting improvements in sigma, Overall Equipment Effectiveness and lead times (Gomaa, 2026).

Considered collectively, the literature evidences a maturation of LSS from terminal- and gate-level interventions towards Industry 4.0-enabled frameworks, AI-driven surveillance and stakeholder-based evaluations, thereby broadening the methodological repertoire for improving port performance.

2.2 Statistical Process Control and port processes

Many of the previously cited papers use SPC as a tool to achieve their stated objectives. SPC has proven to be highly effective in identifying process shifts and understanding process dynamics. Additionally, it uncovers hidden issues, highlighting the necessary steps for ongoing improvement (Gessa *et al.*, 2022; Yuan *et al.*, 2020). Every process inherently exhibits a degree of natural variability caused by the combined effect of unavoidable factors, known as “chance causes.” SPC assists in evaluating this process variability by differentiating between random causes and those that are assignable (Besterfield, 1995; Montgomery, 2009; Shewhart, 1936).

A control chart presents the values of key quality characteristics over time or by sample number. Therefore, the variability of a quality characteristic should be evaluated using output data, which involves estimating its statistical distribution and parameters (Juran and Gryna, 1988).

The standard control chart features a central line (CL), which represents the variable of interest (mean, median, or target value), along with upper control limit (UCL) and lower control limits (LCL), typically established at ± 3 standard deviations from the CL. Its graphical representation is shown in Figure 1.

When a data point exceeds a control limit, specifically falling outside the three-sigma range (Zone B), it is considered a special cause of variation, attributed to the system itself. In the presence of special causes, the process is deemed to be out of control. The area between the UCL and LCL (Zone A) reflects the expected normal variation, known as common cause variation. Common causes, also referred to as “natural” or “random variability,” arise from numerous small, unidentifiable sources of variation. Once assignable or special causes are eliminated, key parameters such as the mean, standard deviation and probability distribution remain stable, indicating the process is “in statistical control” or “under control.” However, abnormal patterns such as trends, sudden shifts, systematic variation, cycles or mixtures may signal the presence of special causes.

There are many types of quality control charts, depending on whether the quality characteristic is a variable or an attribute, and whether one or multiple variables are being monitored (Montgomery, 2009).

In port services, variable charts are the predominant choice, whereas control charts for attributes are used less frequently. Individual and moving range (I-MR) charts have been used in various maritime and logistics contexts. For instance, El Mekkaoui *et al.* (2024) used

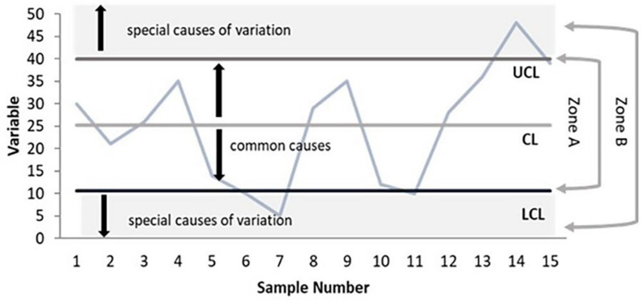

Figure 1. Conventional control chart for monitoring the variability of a process
Source: Gessa *et al.* (2022)

I-MR charts to track vessel arrival patterns, while Nooramin *et al.* (2011) implemented them to alleviate truck congestion and reduce turnaround times. The X-R chart, being the most widely used, has been applied in various studies for diverse purposes. Kusnoaji and Ratih (2021) used it to analyse time motion transactions to improve the quality of container export/import services after the implementation of OCR technologies, while Putra and Ratih (2021) used it to determine the performance of gate operators through the measurement of the time they spend to accomplish their duties. Similarly, Ung and Chen (2010) adopted this technique to examine the current quality level of the cargo handling performance in a container terminal, whereas Yuan *et al.* (2020) also leveraged this tool to evaluate maritime inspections.

Memory-type control charts, such as CUSUM and exponentially weighted moving average, have also been applied in port operations. In a classical setting, Ansorena (2018) demonstrated – through the estimation and control of container vessels' target time in port – that adding memory increases sensitivity to small and sustained shifts relative to I–MR and $\bar{X}$–R charts. More recent studies embed the memory principle within real-time, data-driven monitoring systems based on AIS. Oh *et al.* (2025) evaluate VAE-based monitoring statistics that integrate accumulated historical information to strengthen sequential anomaly detection. Qi *et al.* (2025) incorporate CNN–LSTM architectures that jointly capture spatial patterns and temporal dependence; in effect, they emulate memory charts by dynamically weighting the past evolution of vessel behaviour.

Likewise, multivariate graphs (Hotelling's T^2 Chart) have proven highly effective in monitoring operating conditions and cruise ship CO_2 emissions (Capezza *et al.*, 2019, 2020). To conclude, our review identified only one study that applied attribute control charts, specifically a U-Chart, to track container problems in the exception area and to estimate the average resolution time (Dewi and Ratih, 2021).

Taken together, despite valuable SPC contributions in port services, a gap persists in the joint monitoring of the drivers of turnaround time. Unlike prior research, we consider not only container loading/unloading times but also two complementary throughput metrics – the number of containers handled and crane movements. Although these counts should coincide, operational realities (empty movements, dual container handling and data-recording noise) often decouple them; accordingly, both metrics are retained to provide a more complete signal. We therefore propose and operationalise a multivariate Hotelling's T^2 chart that monitors their joint behaviour and the associated turnaround time components, capturing plan–execution mismatches that univariate or thematic approaches frequently miss. In doing so, we extend a fragmented literature and offer a multivariate framework tailored to container operations that complements univariate charts, memory-type charts and existing thematic applications.

3. Methodology

3.1 Research method

This research adopts a case study methodology, following the DMAIC approach. Case studies are particularly suitable for exploratory research topics and in contexts where existing knowledge is limited (Dubé and Paré, 2003; Yin, 2011).

Developing theory through case studies offers several key advantages, including the generation of novel insights, increased empirical robustness and improved opportunities for theory testing, all grounded in a close interaction with real-world evidence (Eisenhardt, 1989). Furthermore, case studies are often recognised for their analytical rigour, their ability to capture complexity and their potential for validation because of the use of varied data sources – such as interviews, documents, quantitative records and direct observations – collected in naturalistic settings and analysed through comparative frameworks (Annamalah *et al.*, 2025; Eisenhardt and Graebner, 2007; Stake, 1995).

Additionally, case studies serve as a primary source of experiential evidence for the design and continuous improvement of both techniques and theories related to operational excellence (Lameijer *et al.*, 2024).

This research uses a single case study of a port terminal, as it provides the most suitable design for implementing and evaluating SPC in this context. As Yin (2017) highlights, a single case allows for in-depth investigation of a particular setting – such as the container loading and unloading process in a port terminal – by facilitating the collection of rich qualitative and quantitative data on all the elements involved (personnel, sub-processes, activities, technologies, regulations, etc.).

However, even though the single-case approach enhances understanding by examining the phenomenon within one specific organisation or setting (Li *et al.*, 2019), its generalisability may be limited. While multiple-case designs are typically considered more robust, single cases may not always be generalisable (Gijo *et al.*, 2019); nevertheless, well-developed single-case studies remain an accepted and rigorous methodological choice in academic research (Antony *et al.*, 2017; Woodside, 2010). In this regard, the empirical evidence presented in this study is intentionally limited to a single container terminal and to Phase I retrospective analysis, whose purpose is to establish an in-control reference model for monitoring. Accordingly, the framework should be interpreted as a rigorously developed and operationalised monitoring–diagnostic design that demonstrates feasibility and diagnostic value under real operating conditions. Broader external validity would require replication across multiple terminals and prospective Phase II monitoring in additional settings.

We believe that this specific case offers a valuable opportunity to analyse a process under particular and revealing conditions (Eisenhardt, 1989; Flyvbjerg, 2006). The port terminal selected for this case study is strategically located, handles a high volume of traffic and allows close researcher access. This proximity enabled deeper and more frequent engagement with operational data and fieldwork, thereby supporting a detailed examination of process dynamics. The following section presents the main characteristics of the case-study terminal.

An in-depth examination of this case can yield valuable insights into operational dynamics, challenges and potential implications that alternative research methods might not capture. Moreover, such analysis can support theoretical refinement and generate hypotheses for more systematic testing in subsequent multi-case studies (Dubois and Gadde, 2002). Finally, the depth of analysis enabled by a single-case design helps offset the practical limitations associated with accessing multiple port terminals, making it both a feasible and methodologically appropriate choice for the exploratory and applied focus of this investigation.

This study adopts a dual methodological structure in which the Context–Intervention–Mechanisms–Outcome (CIMO) logic (Denyer *et al.*, 2008) provides the overarching analytical framework, whereas the DMAIC cycle operationalises the LSS intervention within the case study. Although each framework fulfils a distinct function, they are intentionally integrated to deliver a coherent design–execution–interpretation pipeline.

The CIMO logic structures the research rationale by clarifying why the intervention should work and under which conditions. In our case, the Context is a port terminal marked by high variability in loading and unloading operations, equipment constraints and fluctuating demand. The Intervention consists of introducing SPC tools – specifically Shewhart control charts – within the DMAIC. The Mechanisms denote the system behaviours triggered by the intervention, including the detection of special causes, heightened visibility of operational instability and the institutionalisation of data-driven decision-making. The intended Outcomes are reductions in cycle-time variability and improvements in container-handling efficiency.

While CIMO frames the explanatory logic, the DMAIC cycle structures how the Intervention (I) is implemented in practice and how data are collected, processed and analysed. In the Define phase, the operational problem and project scope are established within the CIMO-specified Context. The Measure phase details the collection of cycle-time data from terminal information systems, the selection and validation of variables and the use of descriptive statistics and SPC to characterise the baseline, thereby laying the groundwork for identifying Mechanisms. The Analyse phase investigates root causes using control charts, Pareto analysis and cause-and-effect diagrams to determine which Mechanisms account for the observed variation. The Improve phase designs targeted actions to address the Mechanisms that hinder the desired Outcomes. Finally, the Control phase develops SPC-based monitoring plans to sustain performance gains over time.

Through this integration, DMAIC operationalises the Intervention defined under CIMO, while CIMO supplies the interpretive lens through which DMAIC outputs are understood. Accordingly, the results are analysed following the CIMO logic, showing how contextual features condition the effectiveness of the DMAIC-based SPC intervention and how the Mechanisms identified during Analyse lead to the observed Outcomes.

The subsequent methodological sections, specifically the case description and the data collection and processing procedures, are explicitly aligned with this dual framework. The case description specifies the CIMO Context by detailing the operational, infrastructural and organisational characteristics of the port terminal where the DMAIC project is implemented. Understanding these elements is essential to explain why the LSS Intervention is expected to operate through particular Mechanisms and to yield the intended Outcomes. The data collection and processing subsection corresponds to the DMAIC Measure phase and thus operationalises the Intervention within CIMO: it explains how quantitative data were extracted from terminal information systems, how variables were selected and measurements validated and how SPC tools were constructed. These data form the empirical basis for identifying Mechanisms in the Analyse phase and for interpreting the subsequent Outcomes within the CIMO framework. By explicitly linking the case narrative and data-handling procedures to both the CIMO logic and the sequential DMAIC phases, the methodology aligns the two frameworks into a coherent, fully integrated research design.

3.2 Case description

The preceding section underscored the numerous challenges faced by container terminals in their pursuit of enhanced efficiency, which is essential for maintaining competitiveness and ensuring sustainable growth amidst escalating industry competition. This study specifically focuses on the container loading and unloading processes at the port under analysis, aiming to assess how SPC supports its monitoring and controlling.

The port terminal studied is integrated into the Trans-European Transport Network as a Core Port and ranks among the top seven Spanish ports in terms of cargo throughput. Over the past decade, it has also been the second fastest-growing port in Europe. The port's container terminal handles both containerised and roll-on/roll-off cargo. Its strategic geographic position facilitates easy access for maritime vessels. Covering an area of five hectares, the terminal has a capacity of up to 200,000 TEUs (20-Foot Equivalent Units), including refrigerated containers.

The overall process of vessel turnaround is illustrated in Figure 2. Paramount to this process is the maintenance of continuous communication among all stakeholders involved in maritime freight operations, including the shipping company, the vessel's captain and the port authority. Such coordination ensures that all parties are well-informed, thereby minimising delays and operational disruptions often caused by adverse sea conditions or prior port delays. Consistent communication is vital for ongoing monitoring of the vessel's location, assessment of its status and accurate prediction of its arrival time.

During these interactions, the company receives a document detailing the ship's distribution of load and the specific positioning of containers. Throughout loading and unloading operations, each container movement is recorded in the company's internal system, enabling precise tracking of container locations within the terminal yard. This systematic tracking further supports the loading process by providing the ship's captain with a cargo summary document, thus ensuring accurate oversight of the merchandise aboard.

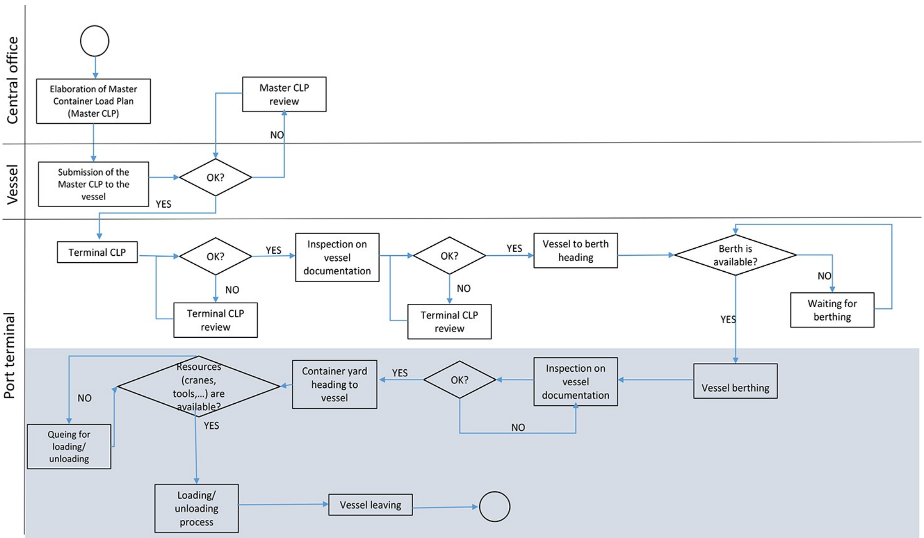

Figure 2. Flow chart of vessel turnaround
Source: Authors' own work

3.3 Data collection procedure

To gather necessary evidence for the study, multiple measurement methods were used. Data was collected mainly from the company's internal records, focusing on key variables.

The company maintains a standardised Port Operations Report presented in a structured table format that documents all activities for each individual vessel. This report captures the full scope of a containership's operations while alongside the berth, including detailed timestamps for berthing, start and completion of cargo-handling operations and departure.

The productivity section records the total number of container moves completed, along with key performance metrics such as Cranes per Hour and Vessel Moves per Hour. The report also provides a comprehensive list of all containers loaded and discharged, including their identification numbers, types, weights and destinations.

Crane utilisation is documented thoroughly, registering operating times as well as idle periods. Finally, the report plays a critical role in logging all delays and operational disruptions, specifying their duration and root causes (e.g. adverse weather, planning issues, or equipment failures).

These records were complemented by on-site observations of operations at the container terminal, which helped verify the data and improve the study's reliability. Collaboration with port operators and logistics managers was essential to better understand current processes. By combining document review and field observations, this study was able to confirm data accuracy and identify main factors affecting performance, such as unnecessary movements, weather issues, human interactions, equipment failures and other disruptions.

The scope of the analysis covered the full calendar year of 2024, during which data were collected for each vessel that docked at the container terminal of the port under study. The data set was then organised to align with the analytical framework of the study, followed by classification and coding procedures. Multiple formats – such as tables and graphs – were used to support statistical processing, using tools such as Excel™ and Minitab™.

The tables used for analysis included, in addition to the operation date and identifying details of each vessel (name, identification/code, route and shipping line), information such as operation times (loading and unloading), delay durations, operational cranes (by type and number of movements) and container data (number, type and status – empty or full). The final data set comprises over 2,000 observations, aggregated by vessel and operation date into a total of 88 records, representing the complete annual port activity. This aggregated data set constitutes the sample used for analysis in the study.

The statistical treatment of the collected data involved applying descriptive statistical methods to generate insights, including measures of central tendency (such as the mean), standard deviation and distributional characteristics. The analysis of the loading and unloading processes for container vessels was conducted using LSS tools, including Pareto charts, time studies, control charts and cause-and-effect analysis.

4. Results

4.1 Define phase

According to the first phase of the DMAIC approach, which is *Define*, the problem is identified, the project objectives are established and the scope of the improvement is defined.

Despite their key role in global supply chains, port terminals continue to face efficiency challenges, with idle time in loading/unloading, creating bottlenecks and substantial economic losses. This case study examines this issue at a specific port terminal where unproductive times are identified, stemming from various factors, including excessive administrative procedures, prolonged truck waiting times and crane inactivity. These inefficiencies require in-depth analysis to support a better understanding of their causes and to identify opportunities for targeted operational improvements.

The unproductive periods, which contribute to both idle time and delays, are categorised into two main types:

(1) Queuing time (Tq_i) is defined as the interval between the vessel's arrival at the terminal and the commencement of loading or unloading operations. This includes the time required for inspections, controls and administrative formalities associated with vessel arrival.

(2) Waiting time (Te_i) refers to the time between the completion of loading/unloading operations and the vessel's departure from the terminal.

A review of the internal operational records from the port terminal analysed in our case study for the year 2024 reveals that unproductive times represent a significant portion of total vessel turnaround time. A comprehensive statistical summary of turnaround time and its components – queuing time, loading/unloading time and waiting time – is presented in Table 2.

The vessels analysed exhibit comparable operative characteristics, encompassing both capacity and length. Consequently, they have been consolidated into a single group to maintain consistency in the process control analysis, which was performed using Minitab statistical software.

Figure 3 illustrates the average proportion of each component contributing to the turnaround time. On average, unproductive time constitutes 24.63% of the total turnaround time, whereas productive time – defined as the duration required to complete the full container loading and unloading process – accounts for 75.37%.

This case study seeks to clearly define and measure the identified problem, providing a basis for further analysis and improvement using the DMAIC methodology.

The objective of this paper is to assess how SPC supports the monitoring and control of container-ship loading and unloading operations within the DMAIC framework. Specifically, the study seeks to determine if the process is under statistical control, which would suggest that variations in operational times are attributable solely to natural causes, rather than systemic failures. Achieving this not only facilitates cost reduction but also directly enhances service quality, an essential factor for maintaining competitiveness in the global maritime transport market.

Table 2. Descriptive statistics of turnaround time and its components (hours)

Variables	Mean	SD	Maximum	Minimum
Turnaround time (tt_i)	17.081	6.210	39.92	6.47
Queuing time (tq_i)	2.869	3.784	21.91	0.01
Loading/unloading time (tl_i)	12.875	5.876	36.95	0.26
Waiting time (tw_i)	1.337	1.501	9.35	0.01

Source(s): Authors' own work

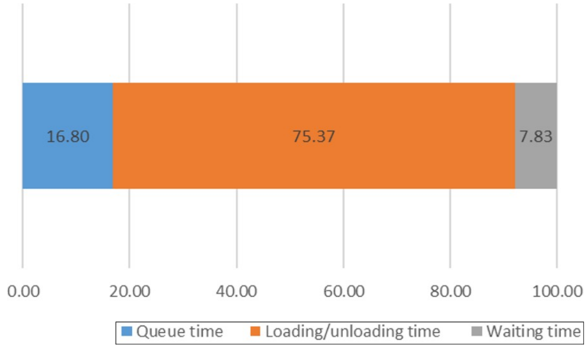

Figure 3. Proportional analysis of turnaround time components ($n = 88$) (% Tt_i)
Source: Authors' own work

4.2 Measure phase

Following the definition of the problem, the next step within the DMAIC cycle is the *Measure* phase. This involves collecting historical data to gain insight into the process targeted for improvement, verifying data availability and sufficiency, documenting the current state and conducting the necessary analysis to support the research objective.

In this case study, the primary goal of the Measure phase is to assess whether the container unloading/loading process at the terminal is under statistical control. To this end, the standard SPC implementation framework – shown in Figure 4 – was applied. The steps within this framework align with those typically performed during the Measure phase of the DMAIC methodology.

First, we identified the critical quality characteristics to monitor; as unproductive time is part of the loading/unloading cycle, turnaround time was chosen as the key variable. Additionally, given that unproductive time may result from crane inactivity or inefficient operation, crane movements were also included as a study variable. Excessive, unnecessary or slow crane movements are all potential contributors to unproductive time.

While, in theory, the number of crane movements should match the number of containers handled – as each movement typically involves lifting, transferring and placing a container – certain factors can cause discrepancies. These include empty moves, handling of double containers or data recording errors. Therefore, both container count and crane movements were included in the analysis to provide a more robust understanding of the process. Table 3 summarises the variables considered.

As multiple quality characteristics were selected, Hotelling's T^2 control chart (Mahalanobis, 1936) was used. This multivariate control chart is widely applied across various industrial settings, owing to its simplicity and effectiveness (Mason and Young, 2002; Yeong *et al.*, 2016). Unlike traditional univariate charts, Hotelling's T^2 accounts for the correlation among variables, improving the detection of out-of-control conditions (Djekic *et al.*, 2015; Hossain and Masud, 2016). It enables simultaneous monitoring of multiple quality characteristics, facilitating integrated analysis of the factors influencing container operations.

In this study, Hotelling's T^2 chart allowed for the concurrent evaluation of the vessel's turnaround time, crane movements and the number of containers handled, offering a comprehensive view of the process performance.

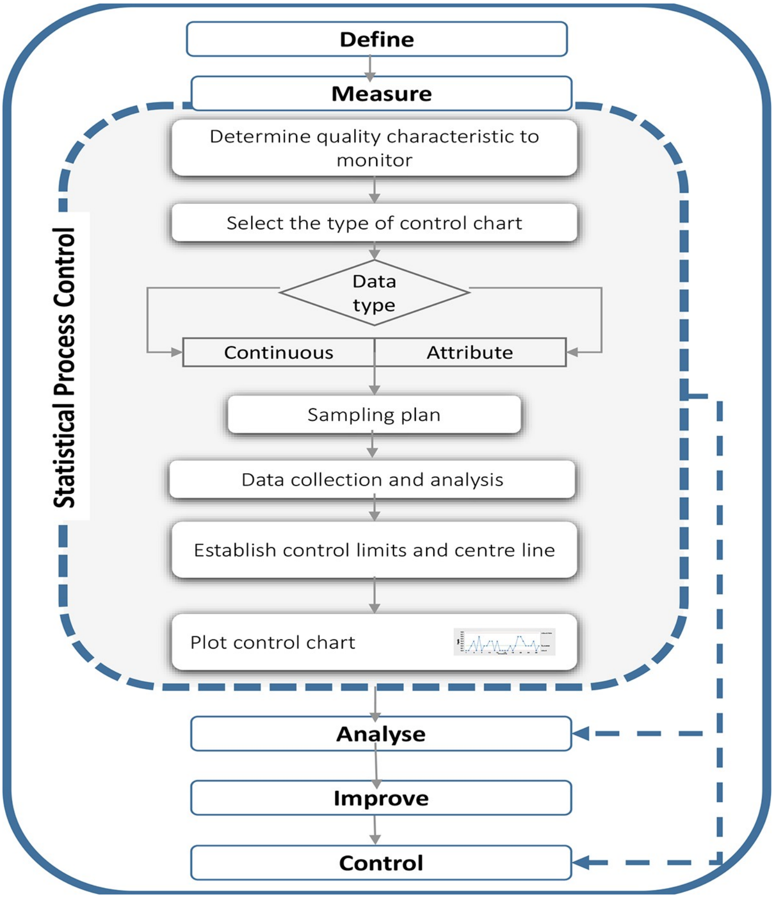

Figure 4. Integrated SPC-DMAIC Methodology
Source: Authors' own work

The multivariate Hotelling's T^2 chart is based on the Mahalanobis distance (Mahalanobis, 1936), calculated as the difference between expected and observed mean vectors. The T^2 statistic is defined as follows:

$$T^2 = \left(X - \overline{X}\right)' S^{-1} \left(X - \overline{X}\right) \quad (1)$$

where X denotes the vector of quality attributes under evaluation:

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \quad (2)$$

is the simple mean vector, and S represents the sample variance-covariance matrix, computed from a set of n observations assumed to be under statistical control:

Table 3. Study variables

Variable	Definition	Formula
Turnaround time (Tt_i)	Total time taken for a vessel to complete all necessary operations at a port terminal, from arrival to departure	Tt_i = vessel's departure time – vessel's arrival time (hours)
Queuing time (Tq_i)	Duration between the vessel's arrival at the terminal and the start of the container loading/ unloading process	*Tq_i = loading/unloading start time – vessel's arrival time (hours)*
Loading/ unloading time (Tl_i)	Time required to complete the full container loading/ unloading process	*Tl_i = loading/unloading end time – loading/unloading start time (hours)*
Waiting time (Twi)	Interval between the completion of the container loading/ unloading process and the departure of the ship from the terminal	*Tw_i = vessel's departure time - Loading/unloading end time (hours)*
Containers ($Cont_i$)	Total number of containers handled in the loading/ unloading process per vessel at the port terminal	$Cont_i = \sum$ containers
Crane movements (Mov_i)	Total number of crane movements per vessel, encompassing loading, unloading and relocation of containers	$Mov_i = \sum$ *[(No. of crane movements per vessel per hour) x (total crane cycle time in hours)]*

Source(s): Authors' own work

$$S = \frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(X_i - \overline{X}\right) \tag{3}$$

The control limit for the T^2 statistic is given by:

$$CL = \frac{p(n-1)(n+1)}{n(n-p)}\ F_{(p,n-p)} \tag{4}$$

where "n" is the number of observations, "p" is the number of quality characteristics and "$F_{(p,\ n-p)}$" denotes the critical value of the F-distribution with p and $n-p$ degrees of freedom.

The application of the Hotelling T^2 control chart is carried out in two clearly defined phases. Phase I involves the analysis of historical data to determine whether the process is stable and to estimate the necessary parameters and control limits. Phase II then uses these control limits to monitor new data from the ongoing process. Establishing a stable data set in Phase I is essential for the accurate estimation of control limits in Phase II (Alfaro and Ortega, 2008). The present study focuses exclusively on Phase I.

Prior to the implementation of the Hotelling T^2 control chart, the underlying distributional assumptions were rigorously evaluated. As an initial diagnostic, marginal normality for each variable was assessed using the Ryan–Joiner test at a 95% confidence level ($\alpha = 0.05$). Additionally, inter-variable dependence was quantified using Pearson correlation coefficients (see Table 4).

Because Hotelling's T^2 is theoretically derived under multivariate normality (MVN), we further assessed MVN using the Henze–Zirkler test. Diagnostics indicated significant departures from MVN. To ensure the reliability of the default upper control limit (UCL = 19.61), a nonparametric bootstrap calibration was performed to estimate the empirical false-alarm probability. The Phase I estimation yielded an empirical exceedance

Table 4. Correlation analysis [Coeff. (*p-value*)]

Variable	Tt_i	$Cont_i$	Mov_i
Tt_i	1 (0.000)	0.750 (0.000)	0.755 (0.000)
$Cont_i$		1 (0.000)	0.975 (0.000)
Mov_i			1 (0.000)

Source(s): Authors' own work

probability of $\hat{\alpha} \approx 0.024$, aligning with the nominal alpha level used under normality for individual observations. This convergence provides empirical justification for the chart's robustness despite the observed distributional violations.

Following the verification of the normality and correlation assumptions, the Hotelling T^2 control chart was constructed using the complete Phase I data set. The resulting chart is presented in Figure 5.

Analysis of the Hotelling T^2 control chart indicates an upper control limit (UCL) of 19.61, with three data points – specifically, samples 3, 45 and 87 – exceeding this threshold.

In Phase I, observations were not excluded solely because they exceeded the UCL. Removals were strictly contingent upon the verification of an assignable cause via the terminal's internal documentation (Port Operations Reports). To establish a stable in-control reference set for estimating control limits, 16 observations associated with documented assignable causes were sequentially removed through an iterative refinement process.

To ensure the absence of systematic bias, the excluded observations were analysed for potential clustering by vessel, route, operator and weather conditions. While the study period monitored a total of six vessels, the signals were distributed across three units, encompassing both shipping companies and geographical routes represented in the sample. The fact that these signals occurred at different points in time and across all operational entities –

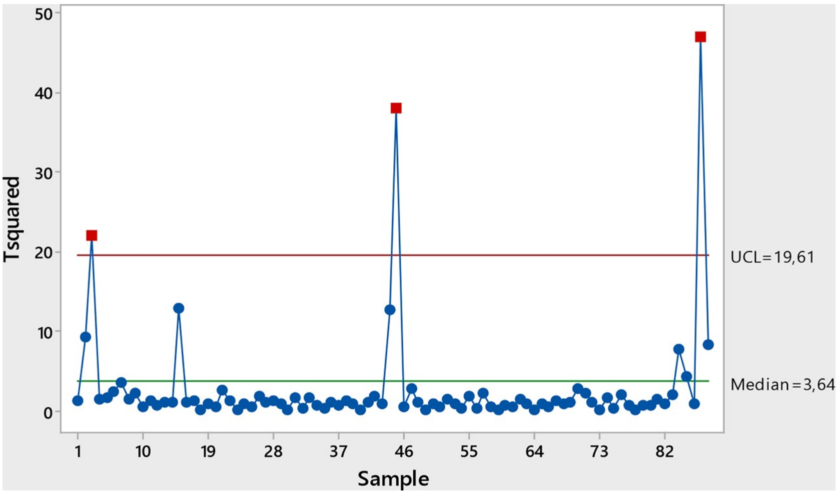

Figure 5. Hotelling T^2 control chart ($n = 88$)
Source: Authors' own work

supported by documented assignable causes – suggests that the variation stems from transient special causes rather than persistent structural differences between vessels or operators. Regarding environmental factors, the impact of adverse weather could not be generalised because of its limited representation in the available records.

Upon removing the outlier observations, the loading/unloading process achieves statistical control. The updated Hotelling's T^2 chart (see Figure 6) confirms that all 72 data points fall below the new upper control limit (UCL) of 19.25. This indicates that the process is under control, as no data exceeds the established threshold, and the chart clearly demonstrates statistical stability.

The in-control subset exhibits 26% and 4% lower average queuing time and waiting time, respectively, compared to the initial out-of-control state (Figure 7). Additionally, the productive time has increased, representing 80% of the turnaround time, up from 75.37% in the out-of-control scenario (see Figure 3).

These parameters should be continuously monitored to ensure the process remains stable under the same initial conditions. To confirm ongoing control, new samples would need to be collected over different time periods for further analysis.

4.3 Analyse phase

In this phase of the DMAIC cycle, we analyse the previous results to identify multivariate patterns, detect abnormal data points and investigate potential root causes of unproductive time during container loading and unloading operations.

The multivariate approach of Hotelling's T^2 chart helps reveal inefficiencies that may not be apparent when each variable is analysed individually. For example, a high turnaround time alone may not be concerning. However, when combined with a high number of crane movements, it may indicate a problem in the operational process. Therefore, points beyond the control limit in the T^2 chart signal operations or time periods where the combination of variables significantly deviates from normal process behaviour.

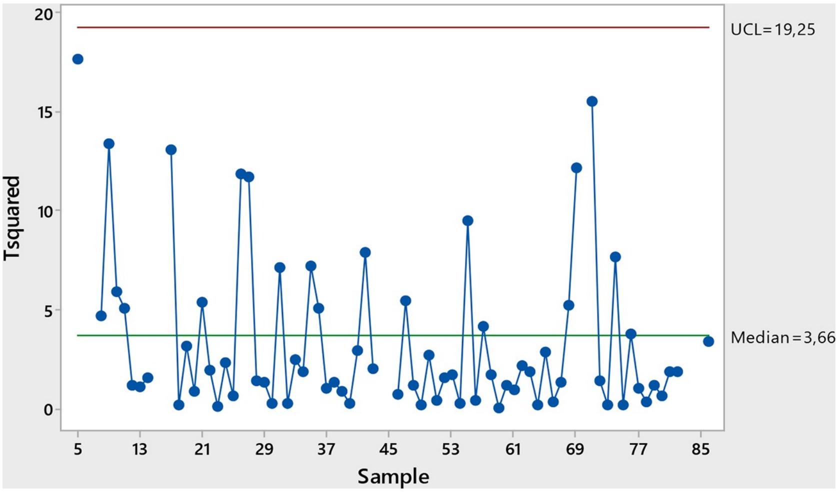

Figure 6. Hotelling T^2 control chart ($n = 72$)
Source: Authors' own work

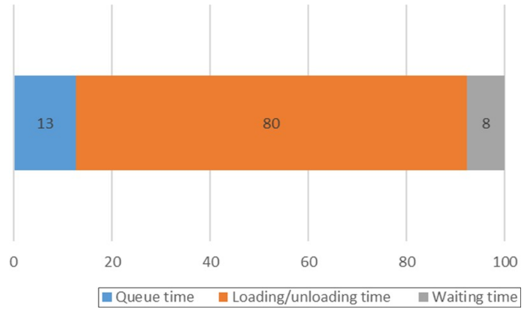

Figure 7. Proportional analysis of turnaround time components ($n = 72$) (% Tt_i)
Source: Authors' own work

In our case study, the review of incidents documented in the Port Operations Reports – which record all activities for each individual vessel – combined with a cause-and-effect analysis (Figure 8), enabled the identification of potential sources of unproductive time in the container loading and unloading process at the port terminal.

The delay factors identified in the diagram (Figure 8) are consistent with findings reported in previous studies (Saeidi *et al.*, 2013; Nwoloziri *et al.*, 2025).

4.3.1 Method. These results indicate that procedural and methodological inefficiencies significantly undermine the terminal's operational performance, suggesting that the observed delays are not incidental but stem from systemic and organisational causes. Stahlbock and Voss (2008) emphasise that the efficiency of a container terminal depends less on the physical speed of cranes and more on the synchronisation of information flows and yard-planning processes. In line with this, the inspections and documentation errors identified in this study function as administrative bottlenecks that introduce non-random, assignable-cause variability into the cycle time (Nwoloziri *et al.*, 2025).

4.3.2 Machines. Equipment deficiencies, such as crane breakdowns and shortages of handling machinery, represent a recurrent source of operational disruption that slows cargo-handling activities and diminishes service quality (Bugaric and Petrović, 2007; Jafari, 2013; Saeidi *et al.*, 2013; Sayareh and Ahouei, 2013; Yousefi *et al.*, 2012). As noted by Rahman *et al.* (2023), limited lifting and handling capacity reduces operational speed, extends the duration of individual handling tasks and indirectly delays subsequent operations.

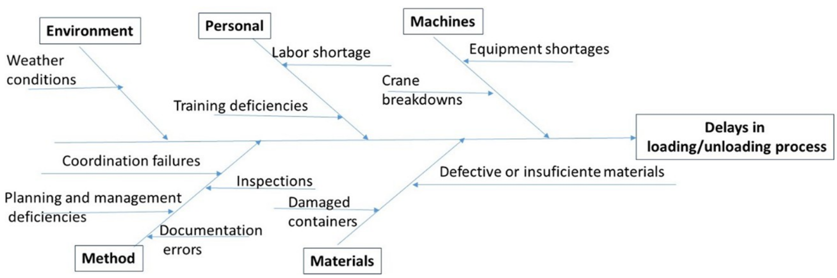

Figure 8. Ishikawa diagram
Source: Authors' own work

4.3.3 Materials. Another source of operational instability relates to material-related factors. Damaged containers and insufficient support equipment interrupt the continuous flow of operations, generating unproductive time due to unplanned tasks such as inspections or urgent re-stowage. As emphasised by Ugboma *et al.* (2004), a port must be adequately equipped to meet customer requirements and sustain its operational performance.

4.3.4 Personal. The analysis also shows that labour-related inefficiencies affect operational performance along two critical dimensions: workforce availability and workforce competence. Staff shortages interrupt the continuous flow of operations, generating waiting times reflected in out-of-control points; at the same time, insufficient training introduces excessive variability in task execution and rework, undermining process standardisation and reducing the terminal's ability to maintain stable cycle times. Di Francesco *et al.* (2015) demonstrate the link between inadequate staffing levels, operational delays and associated cost increases, highlighting how workforce undersupply can significantly disrupt main vessel operations and negatively impact the schedules of the shipping. Moreover, as noted by Pantouvakis and Karakasnaki (2018), the quality of port services is highly sensitive to the technical competence of personnel, reinforcing the need for targeted training initiatives to strengthen the skills of loading and unloading staff (Vicrihadi *et al.*, 2021).

4.3.5 Environment. Finally, it is essential to consider factors beyond the direct control of ports, vessels and cargo owners. Adverse weather conditions, such as strong winds, reduced visibility and tidal variations, lie outside terminal operators' control yet complicate the predictability and planning of port operations (Achurra-Gonzalez *et al.*, 2019). The strong link between extreme weather events and operational disruptions is well established, with such events affecting the punctuality of vessel arrivals and departures and generating significant operational and financial consequences (Danladi, 2020).

The main causes are summarised in the Pareto chart shown in Figure 9, where they are ranked by frequency.

The principal sources of delays in container loading and unloading are bay change, operator change and crane breakdowns, whose resolution would directly address 70% of the problem and indirectly mitigate other identified causes in the study, such as breaks, shift changes, or container unavailability.

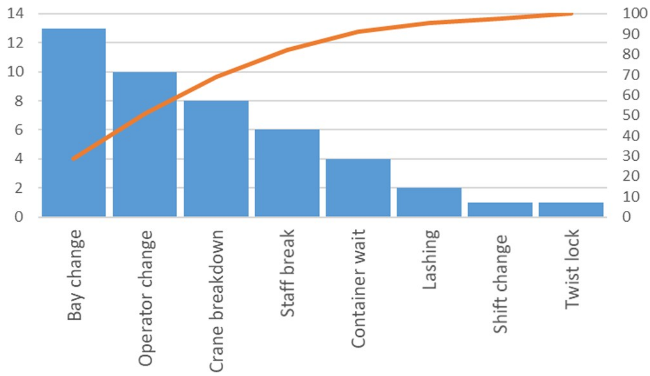

Figure 9. Pareto chart of cause occurrences
Source: Authors' own work

Bay change is the leading cause of unproductive time. It involves moving containers from their initial position to another bay, often because of yard reorganisation, customs inspections, misplacement or last-minute changes in loading plans. This introduces unexpected delays and increases the risk of operational errors.

Operator changes lead to downtime when activities are transferred between workers, typically because of shift changes, breaks, reassignment of tasks or absenteeism. These transitions can disrupt the flow of operations if not managed effectively.

Crane breakdowns were observed in 50% of the out-of-control records, representing a major cause of process interruption. Other less frequent causes include container waiting, staff breaks, shift changes, lashing and twist lock operations, all of which also contributed to inefficiencies during the studied period.

4.4 Improve phase

Following the root cause analysis, the project team prioritised three fundamental drivers of unproductive time – bay changes, operator changes and crane breakdowns – and evaluated candidate countermeasures against explicit improvement criteria. The primary objective is to reduce unproductive time during vessel service. Success is defined by simultaneous reductions in the mean and variability of unproductive time (per crane-hour, per shift and per call), fewer and shorter bay/operator changes and crane-downtime events, improved schedule adherence (lower deviation from plan) and stronger asset performance (higher crane availability and effective throughput, measured as moves per gross hour).

These criteria are monitored via an MSPC control plan that applies Hotelling's T^2 to a core vector comprising turnaround time, crane moves and container count, complemented by contribution diagnostics and supplementary univariate charts. Improvement is evidenced by a favourable centre line shift relative to baseline and the sustained absence of special cause signals over consecutive shifts.

Given the interactions among these causes, an integrated improvement roadmap is proposed (see Table 5), structured around three strategic pillars. These pillars are designed to operate synergistically: processes define the operational requirements, technology provides the necessary tools and human resources ensure proper execution.

The first pillar – process and planning improvement – addresses variability induced by late plan volatility and weak procedural discipline, which underpin bay changes and mis-sequencing. The programme strengthens the advanced planning system to improve the accuracy and timeliness of operator and equipment allocation, thereby reducing last-minute plan changes and crane idle time; standardises procedures for equipment preparation and shift/bay transitions, with systematic audits to verify conformance and detect early deviations; and institutionalises incident management protocols to enable real-time replanning and rapid, low-cost disruption resolution. The causal pathway is straightforward: more reliable plans and disciplined transitions reduce the incidence of bay changes and rehandles, lowering unproductive time and narrowing process variation.

The second pillar – technological enhancement – targets the mechanisms that propagate small planning errors into operational instability and the equipment reliability mechanisms that generate breakdowns. The roadmap deploys intelligent bay allocation and Yard Management capabilities to optimise stowage and positioning given vessel characteristics, cargo mix and equipment availability; improves estimated time of arrival reliability through advanced tracking; leverages the terminal operating system to automate task assignment for cranes and automated guided vehicles with AI-based sequencing to minimise mis-stows; and integrates IoT-enabled predictive maintenance to schedule repairs ahead of critical failures via sensorisation and ML-based diagnostics. Causally, improved information quality and

Table 5. The integrated improvement roadmap

Strategic pillars	Objectives	Improvement actions	Processes	Responsibility
Process and planning improvement	To optimize operational workflows To reduce variability To enhance planning reliability	Review and strengthen the advanced planning system (APS) Standardize operational procedures Implement process audits Establish incident-management protocols Reinforce preventive and predictive maintenance	Load/ unload Communication Maintenance Yard management Berthing and stowage	Operations department Maintenance department
Technological enhancement	To strengthen operational reliability through digitalization, automation and predictive intelligence	Implement intelligent Bay-allocation systems, advanced tracking tools and yard management systems Deploy artificial intelligence -enabled terminal operating system (TOS) Integrate IoT sensors and predictive-maintenance architectures Establish real-time digital and big-data platforms	Diagnostic and maintenance Control and traceability Operational processes	Technologies department Maintenance department
Human resource development	To increase workforce capability To ensure consistent execution To reduce human-related variation	Develop continuous training and upskilling programs Enhance technical and digital skills Implement structured. talent-management and retention frameworks	Training and skill development Safety and prevention Shift and handover management	Human resources department

Source(s): Authors' own work

automated sequencing reduce mis-sequencing and the need for bay changes, while predictive maintenance increases mean time between failures and reduces mean time to repair, directly lowering downtime.

The third pillar – human resource development – focuses on operator learning effects, inconsistency in task execution and turnover-driven variability. The programme establishes comprehensive training and continuous learning for operators and maintenance personnel – emphasising optimal crane operation, strict compliance with standardised procedures and digital competencies for advanced systems – alongside structured talent management practices that stabilise rosters and retain experienced staff. The causal chain is explicit: greater skill, certification and workforce stability reduce changeover penalties and improve procedural adherence, which lowers error rates and compresses process dispersion.

To verify the impact of the improvements and their sustainability over time, and in addition to the control parameters derived from the prior SPC phase (indispensable for assessing the stability of the loading/unloading process), we will track the following common KPIs.

To ensure portability and comparability across contexts – and in line with prior research (Basulo-Ribeiro, *et al.*, 2024; Zajac, 2025) – we draw on the United Nations Conference on Trade and Development (UNCTAD) (2023) standardised framework. Furthermore, because the ultimate objective is to improve terminal performance, we select KPIs from the following categories, consistent with the United Nations proposal:

- Human resources, to measure and evaluate workforce performance and efficiency (level of employment stability, availability of digital tools for advanced training, productivity per employee).
- Vessel operations, to assess the effectiveness and efficiency of port operations related to vessel movement and management (average time in port, average net berthing time, average idle time per ship).
- Cargo operations, to evaluate the effectiveness, productivity and efficiency of loading and unloading processes at terminals (net labour/crane time; productivity per berthing line, average container dwell time at the terminal).

4.5 Control phase

Although the improvement actions remain to be fully rolled out, we propose a pilot control plan to secure sustainability and verify benefits. To ensure stability in the container loading–unloading process, a dual supervision approach will be implemented. First, cycle-time variability will be monitored using a Hotelling's T^2 chart applied to the multivariate cycle-components vector (as specified in the study design), with control parameters pre-estimated from the baseline and updated once the pilot stabilises. Any out-of-control signal or non-random pattern will trigger rapid operational stabilisation and a root cause analysis with a defined closure deadline.

In parallel, we will maintain systematic follow-up of the improvement-plan KPIs to verify target attainment and the sustainability of benefits against the baseline. Data will be captured automatically from operational systems (TOS and associated sources), with real-time dashboards for continuous operational review and short- and medium-term periodic checks within terminal management. To institutionalise the gains, we will conduct periodic audits of standardised procedures (equipment preparation, shift/bay transitions, incident management) and management reviews that incorporate seasonality and resource availability into capacity and staffing decisions.

Accountability for control actions is aligned with the processes defined in the Improve phase (see Table 5). The Operations Department oversees load–unload stability, operational communication, yard management and berthing and stowage coordination; the Maintenance Department ensures preventive/corrective maintenance, diagnostics and equipment availability; the Technologies Department is responsible for the control and traceability of operational processes and for data integrity/quality in the TOS and connected sources; and the Human Resources Department leads training and capability development and the management of shift handovers to sustain standardisation. The Operations Department will act as the plan coordinator and will verify compliance in periodic meetings of a dedicated steering committee, ensuring timely decisions and corrective actions where required.

Finally, consistent with the company's governance, full execution of the Control phase will proceed subject to the organisation's decision to implement the improvement package at scale. Should the organisation proceed, the plan above provides an implementable pathway for real-time monitoring, rapid localisation of variation, targeted response and verified recovery, thereby embedding performance gains in day-to-day operations and supporting continuous optimisation.

5. Discussion

This study presents an integrative SPC–DMAIC framework tailored to container terminal operations, showing how established MSPC techniques can be coherently embedded within a structured improvement cycle to support the monitoring and control of unproductive time during vessel loading and unloading (Figure 10). The contribution of this paper lies in the adaptation and operationalisation of an existing statistical logic to a complex maritime service setting, characterised by high interdependencies among quay, crane and yard activities. Recent reviews of container terminal research emphasise precisely these coordination challenges and the need to translate increasingly rich operational data into

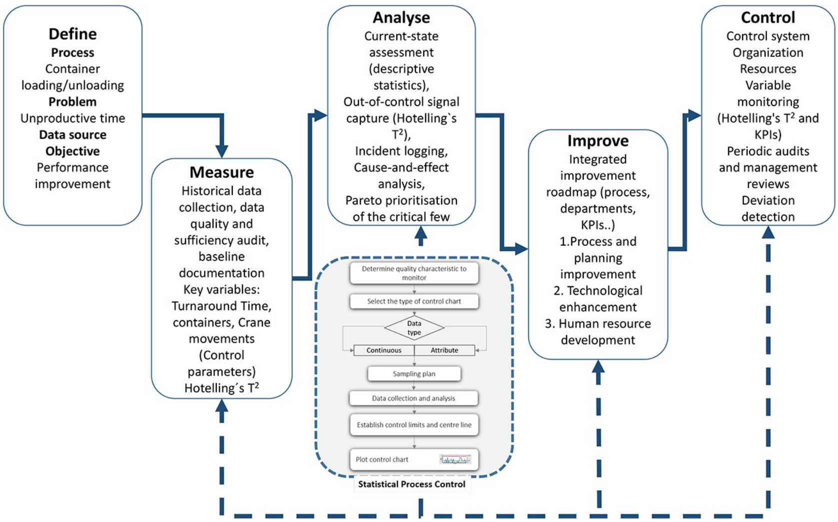

Figure 10. SPC-DMAIC approach to control container handling operations
Source: Authors' own work

actionable control mechanisms, a gap directly addressed by the proposed framework (Weerasinghe *et al.*, 2024).

A central insight of the study is that univariate monitoring proves inadequate in contexts where key performance drivers exhibit strong co-movement and where only their joint behaviour reveals substantive process instability. The MSPC literature shows that techniques such as Hotelling's T^2 – supported by contribution diagnostics and established interpretation methods – are designed to detect changes in the joint distribution of correlated variables and to avoid misleading inferences from isolated chart views (Bersimis *et al.*, 2007). In the empirical setting examined here, a parsimonious multivariate vector comprising turnaround time, crane movements and container count captures the behavioural drivers of unproductive time. The T^2 signals identified departures that were consistent with documented incident records, and subsequent cause-and-effect analysis and Pareto prioritisation translated these statistical signals into dominant operational mechanisms such as excessive or slow crane movements, mis-sequencing and temporary coordination breakdowns (Montgomery, 2009; Antony *et al.*, 2017).

The framework was developed through the integration of three complementary evidence streams:

(1) routinely collected internal operational log data;

(2) direct operational observations and vessel- and shift-level incident documentation; and

(3) planning and execution records used by terminal management.

This integration ensured that MSPC signals were interpreted in light of the operational realities and constraints of terminal operations, thereby addressing a commonly noted limitation of applied MSPC, namely, the gap between detecting statistical signals and determining appropriate operational responses (Bersimis *et al.*, 2007). In this respect, the study reinforces evidence from the quality-management literature indicating that statistical tools create managerial value only when interpreted in conjunction with domain expertise and process knowledge (Montgomery, 2009; Antony *et al.*, 2017).

The proposed framework complements and extends established advances in port planning and scheduling, such as berth allocation and quay crane assignment models, which have traditionally prioritised plan optimisation rather than the continuous statistical control of execution. By embedding MSPC within a DMAIC-based improvement logic, the framework bridges planning and operations: it provides early-warning detection of coupled instabilities during service execution and prescribes reaction rules and performance follow-up mechanisms to stabilise outcomes. In doing so, it responds to calls in recent port research for approaches that integrate data-driven control systems with the coordination realities of terminal operations (Li *et al.*, 2023; Weerasinghe *et al.*, 2024).

In terms of the available evidence, the findings should be interpreted with appropriate restraint. The empirical application is confined to a single container terminal and to Phase I control analysis, which supports the internal coherence, feasibility and diagnostic value of the framework but does not constitute full empirical validation. Accordingly, the framework is best understood as an applied, context-grounded monitoring and diagnostic design; external validity would be strengthened through multi-site replication and Phase II implementation.

Taken together, the framework specifies three mutually reinforcing components: first, a minimal multivariate baseline that avoids false reassurance from apparent univariate stability; second, T^2-based detection and interpretation explicitly aligned with operational knowledge and incident analysis; and third, an SPC-informed monitoring plan linked to the execution and verification of improvement actions. These elements demonstrate how a DMAIC model enhanced with MSPC can support the ongoing monitoring and control of unproductive time in container terminal operations, while maintaining analytical caution in the scope of its claims. Methodologically, the approach aligns with established MSPC traditions; operationally, it equips terminal managers with a statistically grounded and actionable control layer that complements existing planning capabilities and provides a structured foundation for future multi-site and Phase II validation efforts.

6. Conclusions

This paper demonstrates how established SPC techniques can be effectively integrated within the DMAIC improvement cycle to support the monitoring and control of container ship loading and unloading operations in a port terminal context. By applying multivariate SPC to jointly monitor vessel turnaround time, number of containers handled and crane movements, the study illustrates how existing analytical methods can be coherently operationalised to enhance process productivity and managerial decision-making in complex maritime service environments.

From an empirical standpoint, the results indicate that multivariate monitoring provides diagnostic insights that are not attainable through univariate charts, particularly in settings characterised by strong interdependencies among operational variables. The Phase I application shows the feasibility of using MSPC within DMAIC to identify process instability, support root cause prioritisation and inform the design of targeted improvement actions. At the same time, the evidence remains confined to a single terminal and to Phase I control analysis, and the findings should therefore be interpreted with appropriate restraint.

In practical terms, the framework offers terminal managers a structured and implementable approach to integrating data-driven monitoring into continuous improvement routines. By linking SPC signals explicitly to DMAIC decision stages, the approach strengthens the alignment between statistical analysis and operational practice, supporting more systematic control of unproductive time and service variability.

This study also has clear limitations. Its single-case design restricts the transferability of the findings, and the absence of Phase II control prevents assessment of long-term stability and sustainability. Future research should therefore extend the framework across multiple terminals, cargo profiles and automation levels and incorporate Phase II monitoring to evaluate robustness over time. Such extensions would allow for a more comprehensive assessment of the framework's generalisability and managerial impact and would further strengthen its contribution to LSS applications in maritime operations.

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Data availability

The data that has been used is confidential.

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