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Research Article

Efficiency management and control in production system support areas: an approach utilizing the directional distance function and internal benchmarking

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Abstract

Paper aims: This study proposes an approach for continuous and longitudinal analysis and efficiency monitoring in support areas of production systems.

Originality: The study's originality lies in the proposed conceptual model for efficiency assessment and in validating the applicability of DDF as a continuous efficiency monitoring indicator. Furthermore, it includes an empirical discussion on the effect of adding new Decision-Making Units (DMUs) and its impact on shifting the efficient frontier.

Research method: A case-based modeling was conducted in a multinational company in the metal-mechanical sector. The approach applies the Directional Distance Function (DDF) combined with an internal benchmarking procedure.

Main findings: A conceptual model was developed to define system variables, offering potential replication across various support areas. In addition to the conceptual framework, this study presents a practical application and suggests a strategy for communicating efficiency metrics and performance of support areas at all organizational levels through a dashboard designed for continuous efficiency monitoring.

Implications for theory and practice: This research advances existing performance measurement practices by introducing a method to assess the efficiency of support areas. It offers organizations an alternative to the commonly used effectiveness indicators, thereby expanding the scope of performance evaluation.

Keywords

Directional Distance Function. Data envelopment analysis. Efficiency. Support areas of production systems.

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Conflict of Interest

The authors have no conflict of interest to declare.

Ethical Statement

The study involved expert consultations for model validation. No personal or sensitive data were collected, and all participants voluntarily agreed to participate.

Editor(s)

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1. Introduction

Support areas within production systems encompass a broad set of service-oriented functions (including production planning and control, materials planning, maintenance, quality management, logistics, and procurement) that, while not directly involved in the physical transformation of raw materials, are essential to the smooth operation of manufacturing systems (Slack & Brandon-Jones, 2019). Performance indicators commonly used to evaluate these areas include service levels, on-time delivery rates, and inventory level (Gunasekaran et al., 2001).

The service-oriented nature of support areas within production systems makes it difficult to clearly identify their inputs and outputs (Marques et al., 2023). Consequently, assessing the performance of these areas presents challenges for both researchers and managers. To address this issue, several studies have explored which indicators can effectively measure the performance of support areas in production systems (e.g., Abdeen et al., 2022; Andonov-Acev et al., 2008; Kadam & Fonseca, 2009; Mahmood & Mohd Zahari, 2021; Obiajunwa, 2012). In this context, many researchers have reported the use of effectiveness as a common performance indicator (Francis et al., 2011; Kristensen & Saabye, 2021; Naji et al., 2022; Tornese et al., 2014). While effectiveness evaluates the achievement of established goals, it does not account for the resources used to reach those outcomes (Gomes et al., 2023; Dreyfuss & Pinto, 2024). Although monitoring effectiveness is important, it is not sufficient, as this metric fails to consider the optimal use of resources or the optimal generation of outputs (Gomes et al., 2023).

Other performance indicators can also be considered. Key Performance Indicators (KPIs), for instance, help monitor performance in relation to specific critical factors (Star et al., 2016). However, KPIs generally assess factors in isolation, overlooking potential interrelationships and trade-offs (Mapes et al., 1997). Furthermore, the indicators found in the literature, such as effectiveness and KPIs, rarely provide guidance on actions needed to enhance performance, particularly in terms of minimizing costs or maximizing results (Abdeen et al., 2022). These limitations can be addressed by adopting efficiency indicators (Gomes et al., 2023; Camanho et al., 2024). Efficiency offers a comparative measure that quantifies a system's ability to increase outputs or reduce inputs (Charnes et al., 1978; Souza et al., 2018a, b; Sampaio Brasil et al., 2024).

Advancing the measurement of efficiency in support areas of production systems is necessary, especially given the scarcity of practical studies in this domain (Marques et al., 2023; Gomes et al., 2023; Camanho et al., 2024). This need is not new (e.g., Schneeweiss, 1998) and is supported by the increasing share of indirect costs in support activities. For example, support areas may account for approximately 40% of the total costs associated with implementing new technologies in the automotive industry (Rogozhin et al., 2010). Additionally, administrative processes linked to internal and external customer satisfaction can represent 70% to 80% of a company's fixed costs (Monteiro et al., 2017). These figures underscore the importance of evaluating the performance of support areas within organizations.

DEA is the most widely applied technique for assessing productivity and efficiency in systems with multiple inputs and outputs (Peixoto et al., 2017; Camanho et al., 2024; Vogt et al., 2025). Moreover, it does not require assumptions about the production frontier. This method also enables the use of internal benchmarking and allows for the inclusion of both desirable and undesirable outputs (Gomes et al., 2023). Furthermore, DEA provides a promising alternative for measuring the efficiency of support areas in production systems, particularly through external benchmarking of distinct and competing firms (Gomes et al., 2023; Piran et al., 2021).

Despite the growing body of DEA research applied to production systems, most studies employing internal benchmarking have concentrated on manufacturing process (such as assembly lines, fabrication cells, and supply chains) where inputs (e.g., labor, energy, raw material) and outputs (e.g., production volume, finished goods) are more straightforwardly quantifiable (Piran et al., 2020; Camanho et al., 2024). In contrast, support areas, characterized by their service-based nature, the intangibility of many outputs, and their cross-functional scope, present distinct challenges for efficiency modeling: the absence of a physical transformation process makes it more difficult to define comparable Decision-Making Units (DMUs) and to establish meaningful performance frontiers (Marques et al., 2023; Gomes et al., 2023). When external benchmarking is not feasible, internal benchmarking enables longitudinal comparisons of Decision-Making Units (DMUs) with themselves (Camanho et al., 2024). However, most DEA studies using internal benchmarking focus on manufacturing processes (Piran et al., 2020). To our knowledge, no studies have proposed a framework for continuous efficiency evaluation and monitoring in support areas of production systems using either classical DEA or its variant, the DDF, combined with internal benchmarking.

These characteristics of DEA (its flexibility in handling multiple inputs and outputs without requiring distributional assumptions, its support for internal longitudinal benchmarking, and its capacity to incorporate both desirable and undesirable outputs) make it particularly well-suited to address the identified gap in the evaluation of support area efficiency.

This study aims to propose an approach for longitudinal and continuous analysis and monitoring of efficiency in support areas of production systems. A case-based modeling was conducted in a multinational company in the metal-mechanical sector, using the DDF along with internal benchmarking procedures. The study offers three main contributions. First, it introduces a conceptual model for efficiency assessment and demonstrates the applicability of the DDF as a continuous efficiency monitoring indicator. Second, it provides an empirical discussion on the impact of adding new DMUs on the displacement of the efficient frontier. Third, from a managerial perspective, it presents a dashboard to track the performance outcomes of support areas. This approach enables companies to go beyond effectiveness-based evaluations by incorporating efficiency as a key performance metric.

The remainder of this paper is structured as follows: Section 2 presents the theoretical background on performance evaluation in support areas of production systems. Section 3 describes the methodological procedures, including the case-based modeling approach. Section 4 presents the results, focusing on gains, losses, and efficiency, as well as the efficiency management dashboard. Section 5 discusses the findings, and Section 6 concludes the study.

2. Theoretical background

2.1. Performance measurement and management

Performance measurement and management is a long-established domain in operations management, and it affirms that a good measurement system and its indicators must quantify the efficiency and effectiveness of actions using key dimensions such as quality, time, cost, and flexibility (Neely et al., 2005). Building on this foundation, performance management frameworks integrate indicator selection, target setting, monitoring, and feedback into structured cycles of continuous improvement (Franco-Santos et al., 2012; Nudurupati et al., 2011; Götz et al., 2023).

The selection of appropriate indicators is a significant challenge, as measurement systems must be multidimensional to cope with the increasing complexity of organizations and dynamic enough to adapt to changes in the business environment (Kennerley & Neely, 2002). This complexity becomes particularly evident in the support areas of production systems, understood as organizational units that do not directly transform raw materials into finished goods but provide essential enabling services such as materials planning and control, maintenance, logistics, quality management, and procurement (Slack & Brandon-Jones, 2019). The following section reviews selected empirical and applied studies on performance evaluation in these contexts.

2.2. Related studies on performance evaluation in support areas

The academic literature presents several studies that emphasize the relevance of efficiency indicators in support areas of production systems, highlighting both their benefits and challenges. Several studies (Bianchi, 2012; Naji et al., 2022; Star et al., 2016; Tornese et al., 2014) contributed to the development of performance evaluation systems by presenting frameworks to support the selection of relevant indicators. However, none of these studies provided practical applications of the proposed frameworks.

Beyond proposing frameworks, the literature also identifies specific criteria that should guide indicator selection in support areas. According to Andonov-Acev et al. (2008), these include: (i) the intended message the indicator communicates; (ii) the decisions required when performance falls below expectations; (iii) the individual or group responsible for making these decisions; and (iv) the processes and infrastructure needed to ensure effective monitoring.The authors further emphasize that awareness of performance indicators should not be limited to senior management. All personnel within the department should understand the indicators and how they align with organizational objectives (Andonov-Acev et al., 2008).

In a pioneering study, Loch & Tapper (2002) were among the first to explore key indicators for monitoring the efficiency of a Research and Development department within an industrial context. They proposed tracking 16 indicators in a single chart and reported improved effectiveness in the department after one year of monitoring, with all indicators showing notable improvement (Loch & Tapper, 2002).

Kadam & Fonseca (2009) introduced a conceptual model tailored for the Oil and Gas industry in the Middle East. This model outlined procedures for defining, collecting, measuring, and communicating metrics to ensure alignment between strategic and operational goals across company departments and the organization's overall objectives (Kadam & Fonseca, 2009).

Several approaches have been applied across different sectors. For example, Alsyouf (2006) developed a strategic system to monitor performance in the maintenance planning department. Obiajunwa (2012) assessed the

performance measurement process of maintenance project departments across six companies but did not delve into the recurrence of performance indicators. Martin et al. (2012) examined the financial planning department of a multinational metal-mechanical company with the aim of presenting an indicator to evaluate the quality of data produced by the department. However, the study did not detail the implementation pathway for the indicator. Abdeen et al. (2022) investigated the supply chain departments of three hotel networks, conducting interviews with 21 specialists and identifying 38 relevant performance indicators.

Kristensen & Saabye (2021) aimed to validate performance improvements in the administrative sector of an industrial company following Lean implementation. They calculated the ratio between completed tasks and the budgeted and consumed resources, defining this metric as efficiency. It is worth noting that the authors only considered time as a resource and overlooked other important aspects, such as whether tasks were completed within the designated timeframe (Kristensen & Saabye, 2021). Ghosh et al. (2016) proposed a dashboard to monitor clients by categorizing key performance indicators (KPIs) based on importance. The dashboard enables users to compare the current month's results for one or more clients with the previous month's, thereby facilitating the identification of KPI improvements or deteriorations (Ghosh et al., 2016).

Another approach involves aggregating multiple indicators into a single metric, known as a composite indicator (Francis et al., 2011; Ghosh et al., 2016). This method yields a simplified and more comprehensible metric, albeit less informative than the full set of original indicators (Mariani et al., 2024). In this context, Francis et al. (2011) focused on the building maintenance sector and proposed a composite indicator derived from the arithmetic mean of various aspects of building upkeep.

Other studies have either proposed a single indicator or the combination of multiple indicators into one metric (Francis et al., 2011; Ghosh et al., 2016; Kristensen & Saabye, 2021; Namba et al., 2007). Additionally, some research has suggested consolidating indicators into a report (Naji et al., 2022; Tornese et al., 2014), while others have sought to determine which indicators should be analyzed in support areas (Abdeen et al., 2022; Andonov-Acev et al., 2008; Kadam & Fonseca, 2009; Martin et al., 2012; Obiajunwa, 2012). Several studies have also proposed frameworks to assist in the selection of indicators (Alsyouf, 2006; Bianchi, 2012; Loch & Tapper, 2002; Star et al., 2016).

Table 1 provides a summary of the literature, categorizing the indicators used in research on performance measurement in support areas of production systems. The classification highlights a concentration of studies utilizing effectiveness indicators. Moreover, only Loch & Tapper (2002) & Ghosh et al. (2016) conducted longitudinal evaluations of the studied departments. This finding underscores a gap in the literature regarding performance indicators specifically designed for longitudinal evaluation of support areas with a focus on efficiency.

Table 1. Classification according to the type of indicator proposed.

Author	Title	Classification
Abdeen et al. (2022)	A framework for facilities management supply chain performance evaluation: case study of hotel buildings	Efficacy
Obiajunwa (2012)	A framework for the evaluation of turnaround maintenance projects	Efficacy
Tornese et al. (2014)	A systematic framework for defining environmental performance metrics for industrial services	Efficacy
Francis et al. (2011)	Assessing The Effectiveness of Maintenance Practice, In Caring For Historic Buildings	Efficacy
Ghosh et al. (2016)	CoCOA: A Framework for Comparing Aggregate Client Operations in BPO Services	Effectiveness
Naji et al. (2022)	Construction changes order management project support system utilizing Delphi method	Efficacy
Martin et al. (2012)	Decision support services based on dynamic digital analyses: Quality metrics for financial planning processes	Efficacy
Bianchi (2012)	Enhancing performance management and sustainable organizational growth through system-dynamics modelling	Efficacy
Andonov-Acev et al. (2008)	Enterprise Performance Monitoring	Efficacy
Loch & Tapper (2002)	Implementing a strategy-driven performance measurement system for an applied research group	Efficacy
Kristensen & Saabye (2021)	Increasing the enabling use of performance measures: a longitudinal quasi natural experiment	Effectiveness
Alsyouf (2006)	Measuring maintenance performance using a balanced scorecard approach	Efficacy
Star et al. (2016)	Performance Measurement and Performance Indicators A Literature Review and a Proposed Model for Practical Adoption	Efficacy
Namba et al. (2007)	Technologies for Raising Efficiency in Support Services	Effectiveness
Kadam & Fonseca (2009)	The E&P Balanced Scorecard: Becoming a Strategy Focused OPCO Driven by Performance	Efficacy

This gap is particularly significant considering the performance management literature, which emphasizes the need for dynamic, recurring measurement systems capable of detecting deterioration trends and supporting timely corrective action (Kennerley & Neely, 2002; Franco-Santos et al., 2012). The present study addresses this gap by applying the Directional Distance Function as a longitudinal efficiency monitoring tool in a production support area.

2.3. Distance Directional Function (DDF) model

Traditional DEA models, like CCR model (Charnes et al., 1978) and BCC model (Banker et al., 1984) measure efficiency as a radial contraction of inputs or a radial expansion of outputs toward the production frontier, depending on the model orientation. While widely applied, these models present three limitations that are critical in the context of the present study: (i) they do not natively incorporate undesirable outputs within the same optimization problem; (ii) radial projections impose equal proportional adjustments across all variables, which may not reflect real operational constraints; and (iii) efficiency scores are calculated relative to the reference technology (frontier) of a specific period, which causes mathematical and comparability issues in longitudinal analyses when production frontier shifts over time do to technological progress (Chung et al., 1997; Zhou et al., 2008).

The Directional Distance Function (DDF) addresses these limitations by allowing the analyst to specify a directional vector that simultaneously expands desirable outputs and contracts undesirable outputs for a given level of inputs, providing a basis to evaluate productivity changes over time (Chung et al., 1997). So, to account for both desirable and undesirable outputs, the DDF model was adopted.

The non-oriented DDF model simultaneously aims to minimize inputs, maximize desirable outputs and minimize undesirable outputs (Ramli et al., 2013). In Equation 1, the DDF is presented with the directional function $D\rightarrow$. Equations 2 and 3 specify the constraints for desirable outputs (which we seek to increase) and undesirable outputs (which we seek to decrease), respectively. Equation 3 also refers to the inputs, while Equation 4 addresses the combination of DMUs. Equation 5 is a nonnegativity restriction (Chung et al., 1997).

$$\rightarrow D\left(y,b,x;g\right)=max\,\delta \tag{1}$$

Subject to:

$$s.t.\sum_{j=1}^{n} y_{rj}\,\lambda_j \geq y_{rj0}+\delta\, g_y \qquad r=1,\ldots,s \tag{2}$$

$$\sum_{j=1}^{n} b_{kj}\,\lambda_j = b_{kj0}-\delta\, g_b \qquad k=1,\ldots,l \tag{3}$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{rj0}-\delta\, g_x \qquad i=1,\ldots,m \tag{4}$$

$$\lambda_j \geq 0 \qquad j=1,\ldots,n \tag{5}$$

where:

λ_j = weight assigned to DMU j;
y_{rj} = amount of output r observed in DMU j;
y_{rj0} = amount of output observed in the evaluated DMU;
b_{kj} = amount of undesirable output r observed in DMU j;
b_{kj0}= amount of undesirable output observed in the evaluated DMU;
x_{ij} = amount of input i observed in DMU j;
x_{rj0} = amount of input observed in the evaluated DMU.

It seeks to expand desirable outputs (yg) while reducing inputs (x) and undesirable outputs (yb), based on a directional vector g ($-x$, $-yb$, yg) (Chung et al., 1997).

The DDF model also enables the derivation of efficiency targets, the theoretical output values that each DMU could achieve while maintaining its current input levels, obtained by projecting each DMU onto the efficiency frontier along the specified directional vector (Färe et al., 1994). The potential gain for each variable is defined as the difference between the projected target value and the observed value, providing a concrete and operationally interpretable measure of improvement potential for each DMU in each period (Ramli et al., 2013).

3. Methodological procedures

This study adopts a case-based modeling approach, which posits that it is possible to construct objective models capable of explaining process behavior or capturing the decision-making challenges faced by operational managers in real-world settings, either partially or holistically (Karlsson, 2023). Models developed through this approach can be validated using real processes, thereby confirming both the quality of the model and the feasibility of the proposed solutions (Karlsson, 2023).

Case-based modeling is particularly suited to this study because it enables model development grounded in authentic operational contexts, where variables, constraints, and decision-making logic are drawn directly from practice. This approach is especially appropriate when the research objective involves both explaining how a system operates and designing a solution (in this case, a longitudinal efficiency measurement model) that can be tested and validated within that same system (Karlsson, 2023; Bertrand & Fransoo, 2002).

The working method is detailed in Figure 1, follows six key stages: (i) problem definition and conceptualization, (ii) conceptual model and variable definition, (iii) model resolution, (iv) test and validation, (v) discussion of the results, and (vi) implementation. These stages are consistent with the case-based modeling framework proposed by Mitroff et al. (1974), further operationalized for quantitative operations management research by Bertrand & Fransoo (2002) & Karlsson (2023).

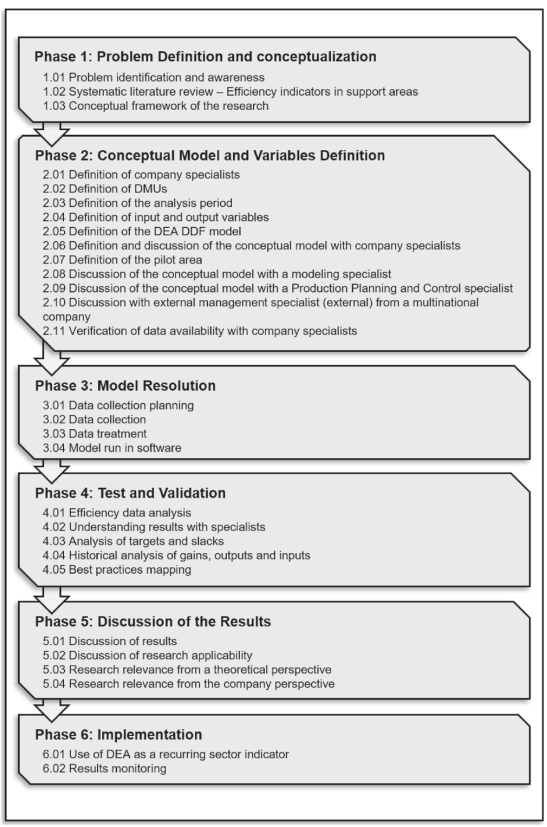


Figure 1. Working method.

As shown in Figure 1, the problem definition and conceptualization stage was informed by a Systematic Literature Review (SLR) conducted to map existing studies on efficiency evaluation in support areas of production systems. The SLR followed a structured protocol covering search string definition, database selection, and eligibility criteria. The full protocol, search results, and quality-assessment procedures are described in Appendix A.

Also, the problem definition and conceptualization stage involves the development of a conceptual model of the problem and a deeper understanding of the system under study. In this phase, the scope of the problem and the model are defined, along with the variables to be included in the analysis. In the modeling phase, a quantitative model is constructed, and the causal relationships between variables are established. The model resolution stage involves the mathematical computation of the model. In the final stage, the model outputs are tested and implemented. (Mitroff et al., 1974; Bertrand & Fransoo, 2002).

3.1. Problem definition and conceptualization

Before presenting the empirical case, it is necessary to clarify the concept of 'support area' as adopted in this study. Support areas are organizational units that do not directly transform raw materials into finished products but provide essential enabling services to production operations (such as production planning and control, materials planning, coordination, logistics management, and inventory control) (Slack & Brandon-Jones, 2019). This distinction differentiates support departments from manufacturing process areas, which are the more common focus of DEA efficiency studies, and directly motivates the research gap explored here.

For the exploratory phase of this study, a case-based model was developed using real data from a support department of a company in the metal-mechanical sector, which manufactures motorized tools. The subject of this case is a multinational firm headquartered in Europe, with production facilities in seven countries, including Brazil. The Brazilian unit, located in Rio Grande do Sul, comprises two main business segments: motors and cylinders. The motor segment is responsible for machine assembly, with an installed capacity of 1.1 million machines per year. The cylinder segment produces 90% of the group's cylinders, with a capacity exceeding 11 million units annually.

The research focuses on the Planning and Control of Materials and Production (PCMP) department of the Brazilian production unit, considering its influence on both business segments. This department handles various functions, including production planning and control, inventory management, material planning, air freight management, service-level compliance, and supply to distribution centers. Although the PCMP department is closely coupled with production operations, it is classified here as a support area because it does not perform physical transformation of materials. Instead, it provides planning, coordination, and inbound logistics services that enable the production system to function effectively (consistent with the support-area definition adopted above). This classification also clarifies what distinguishes this study from DEA applications focused on manufacturing processes: the inputs and outputs modeled here capture the performance of a planning and coordination function, not a physical transformation process.

The DEA model was developed with the assistance of experts from the company, in line with recommendations from the literature (Piran et al., 2021). Two groups of experts were consulted: external specialists with experience in modeling (Table 2) and internal specialists with in-depth knowledge of the processes under study (Table 3).

Table 2. External specialists group.

Specialist	Area of Expertise	Support Provided
Specialist 1	PhD in Production Engineering and Systems – Modeling Specialist	Conceptual model development and validation
Specialist 2	PhD in Production Engineering and Systems – Specialist in Production Planning and Control	Conceptual model validation; Empirical model development and validation
Specialist 3	PhD in Production Engineering and Systems – Expert in management of multinational companies in the metal-mechanical sector and DEA	Conceptual model validation; Empirical model development and validation

Table 3. Internal specialists group.

Role	Project Contribution	Years in Company
Vice President of Operations	Validation of the model and data panel	26
Supply Chain Director	Model definition and results interpretation	9
Planning Specialist	Model definition, data collection, model validation, and results interpretation	6

Table 3. Continued...

Role	Project Contribution	Years in Company
Manager of Materials and Production Planning and Control	Model definition, validation, and results interpretation	11
Production Planning Analyst	Model definition, data collection, validation, data panel development, and results interpretation	8
Material Planning Analyst	Model definition, data collection, validation, data panel development, and results interpretation	5
Sales and Operations Planning Analyst	Model definition, data collection, validation, software application, data panel development, and results interpretation	4

As this is a longitudinal study, defining the time horizon was a crucial step. Reliable data availability was the primary criterion. Based on consultations with internal experts, the period from January 2018 to August 2024 was selected. Monthly data were used as Decision-Making Units (DMUs), resulting in 80 DMUs: (i) 12 from 2018, (ii) 12 from 2019, (iii) 12 from 2020, (iv) 12 from 2021, (v) 12 from 2022, (vi) 12 from 2023, and (vii) 8 from 2024.

3.2. Conceptual model and variable definition

For the selection of input and output variables, both external (Table 2) and internal experts (Table 3) were consulted, as recommended by Casu et al. (2005). A conceptual model was initially developed to guide the identification of relevant inputs and outputs for assessing the efficiency of support departments (Figure 2)

In this model, outputs represent the department's deliverables that directly affect company performance. These can include both desirable and undesirable outputs. Desirable outputs are those whose increase positively influences organizational outcomes, whereas undesirable outputs are those where lower values are preferable. In Figure 2, the asterisk (*) denotes a system resource needed to achieve the output. While the variables identified as (**) are those under the sector's responsibility, directly impacting the supported system, and may be desirable (the higher, the better) or undesirable (the lower, the better).

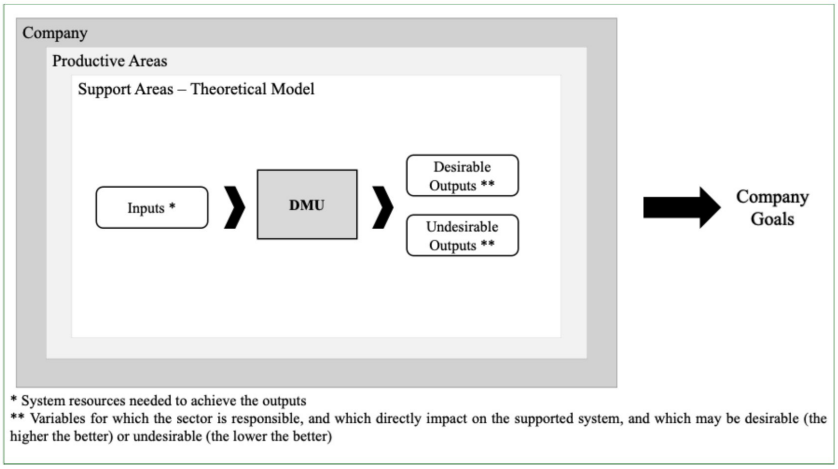


Figure 2. Conceptual model for identifying inputs and outputs.

Once relevant outputs were identified, input resources consumed by the support department to achieve these outputs were defined. The selection of inputs reflects the controllable resources within the PCMP department's direct scope of responsibility: personnel costs (staffing and compensation decisions managed by the department), raw material inventory costs (determined by replenishment policies under the department's control), and inbound logistics costs (managed through freight contracts and air freight authorization decisions). These inputs are consistent with prior efficiency studies in logistics and supply chain management using DEA (Alsyouf, 2006; Obiajunwa, 2012; Abdeen et al., 2022).

This conceptual model can be applied to evaluate the efficiency of any support department, not only the pilot area investigated in this study. Thus, the conceptual model presented here represents a key contribution of this research.

The conceptual model (Figure 2) served as the foundation for the DEA analytical model employed in this study (Figure 3). This DEA model was refined and validated in five rounds of evaluation with both internal and external experts. The five rounds followed a structured iterative protocol: in rounds one and two, external specialists reviewed the conceptual model (Figure 2) and proposed adjustments to the output structure. In rounds three and four, internal experts assessed the operational feasibility of each variable, confirmed data availability in the company's systems, and validated measurement methods. The fifth round consolidated the model into its final form (Table 4). Between rounds, the model was revised based on specialist feedback before being resubmitted for evaluation. Data availability was also confirmed with the company.

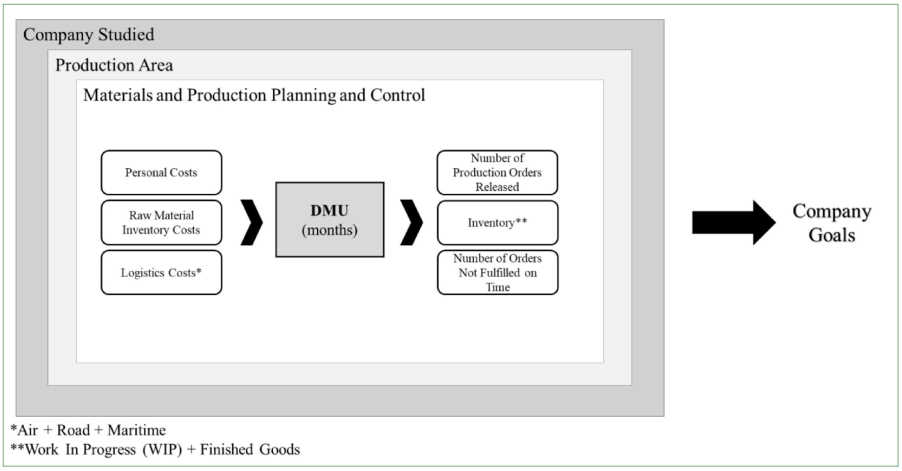


Figure 3. DEA DDF model used in the study.

Table 4. Data collection procedure.

Variable Name	Calculation Method	Previous studies
Personnel Cost ($x1$)	Total personnel cost for the sector during the period, including analysts, specialists, and the supervisor of the production and materials planning and control area. The cost includes salaries and compensatory time.	Alsyouf (2006); Obiajunwa (2012)
Raw Material Inventory Cost ($x2$)	Sum of inventory value for raw materials, both imported and domestic, during the period.	Alsyouf (2006); Bianchi (2012); Abdeen et al., (2022)
Logistics Cost (air + regular) ($x3$)	Total inbound logistics cost, combining air freight (used only in exceptional cases) and regular freight, either maritime or road, according to supplier contracts for raw material transport.	Alsyouf (2006)
Released Production Orders ($yb1$)	Total value of production orders released during the month.	Obiajunwa (2012); Kristensen & Saabye (2021)
Work-in-Progress (WIP) and Finished Goods Inventory (-) ($yb2$)	Total inventory of work-in-progress and finished goods, considering the three distribution centers (São Leopoldo, São Paulo, Benevides) at the end of each period.	Alsyouf (2006); Bianchi (2012); Abdeen et al., (2022)
Unfulfilled Orders (-) ($yb3$)	Total number of missed order lines, those not delivered in the requested quantity or date due to stock unavailability.	Obiajunwa (2012); Kristensen & Saabye (2021)

The efficiency levels were estimated assuming constant returns scale (CRS), given the comparability of batches in terms of scale size. This is inherent to internal benchmarking, where the unit of analysis is compared with itself over time (Piran et al., 2021).

3.3. Model resolution and data analysis

The data collection procedure consists of four stages. The first involves defining the variables, as presented in Table 4. The second establishes the data sources, namely SAP (Systems Applications and Products in Data Processing) and the internal system. The third stage addresses missing data, which were removed from the dataset. The fourth stage concerns the detection and correction of errors and inconsistencies.

After defining the variables used in the DEA model, the internal group of experts reconvened to develop a detailed and appropriate plan for collecting data on each variable. Table 4 presents information on each variable, including the corresponding system or data source consulted.

Two variables in the model are classified as undesirable outputs: WIP and Finished Goods Inventory (*yb2*) and Unfulfilled Orders (*yb3*). The treatment of undesirable outputs in DEA follows the approach formalized by Färe et al. (1994), in which outputs that should be minimized are incorporated into the DDF framework with reversed directionality (the model penalizes their increase rather than rewarding it).

Excess WIP and finished goods inventory is classified as undesirable because, in the company's lean production context, inventory beyond optimal service-level targets generates carrying costs, capital immobilization, and obsolescence risk. The goal is not to minimize inventory to zero but to maintain it within efficient bounds, which is a distinction that the DDF captures naturally by measuring deviations from the efficient frontier rather than applying absolute minimization. Inventory minimization does not operate in isolation: because unfulfilled orders are simultaneously modelled as an undesirable output, the directional vector does not reward inventory reductions that would raise unfulfilled orders under high replenishment-lead-time variability, thereby preserving the department's service performance. Although WIP and finished-goods levels partly depend on production batch sizes, batch sizing in the studied company falls within the materials planning area, so the resulting inventory remains controllable, consistent with its treatment as an undesirable output.

Unfulfilled Orders (*yb3*) are classified as undesirable because each unfulfilled order line directly signals a failure in materials planning and replenishment, which falls within the PCMP department's direct control. While production capacity constraints, quality issues, and process variability may also contribute to order non-fulfillment, these factors fall under the jurisdiction of production and quality departments and are outside this model's scope. Within the PCMP department, the primary controllable factor for reducing unfulfilled orders is raw material replenishment planning, this justifies the inclusion of Raw Material Inventory Cost (x_2) as the input most directly associated with this output (Cooper et al., 2007).

Table 5 shows the collected data, including average, median, and standard deviation for each variable. A notable difference exists between the measurement units of the variables. To standardize these measurements, inventory values (raw materials and finished products), along with logistics cost, were divided by 1,000 and used in the model as values in millions of BRL.

Table 5. Descriptive statistics of the variables.

	Input			Output		
	Personnel Cost (BRL)	Raw Material Inventory Cost (M BRL)	Logistics Cost (M BRL – air + road + maritime)	Released Orders	Inventory (M BRL – Work in progress (WIP) + Finished Goods)	Unfulfilled Orders
Mean	215,406	241,114	4,125	361	238,726	4,909
Median	213,684	244,409	2,636	356	204,852	4,266
Std. Dev	50,581.5	96,554.7	3,256.8	84,4	106,056.4	4,104.4

Efficiency scores were calculated using RStudio. The relative efficiency of each DMU, along with their target values, improvement potential, and corresponding benchmarking DMUs (for those identified as inefficient), were compiled into a new spreadsheet for subsequent analysis. Target values represent the theoretical points on the efficient frontier that each DMU is projected along the specified directional vector, computed directly from the DDF model output (Chambers et al., 1996). The potential gain for each DMU is defined as the difference between its actual output value and the corresponding frontier target, quantifying the magnitude of improvement required to achieve efficiency (Cooper et al., 2007). The analysis process followed the procedure illustrated in Figure 4.

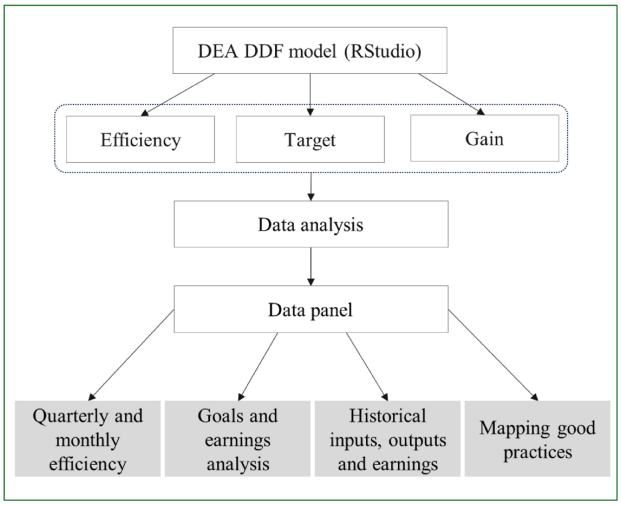


Figure 4. Procedure for results analysis.

It is important to emphasize that we assume the DDF model to be non-oriented, aiming simultaneously to minimize inputs and maximize outputs (Ramli et al., 2013). Based on the efficiency data calculated with the DEA model and using internal benchmarking, the results were organized into a data dashboard. This structure was designed to facilitate interpretation by researchers, managers, and other stakeholders. Analyses were performed monthly and organized into four distinct stages, each aligned with specific objectives.

Also, there is a methodological limitation of the DDF model in longitudinal applications: the inclusion of new DMUs alters previously computed efficiency scores, since the efficient frontier is recalculated with each additional observation. In this study, this limitation was mitigated through the design of the dashboard (Section 4.2), which archives historical efficiency values and preserves previously computed scores, thereby maintaining the traceability of each measurement to the frontier under which it was generated and supporting consistent longitudinal monitoring. This design decision is further discussed in Section 5.

4. Results

4.1. Analysis of efficiencies, targets, and gains

Appendix B presents the monthly efficiency results in chronological order. Thirty-four DMUs achieved full efficiency (100%), accounting for 42.5% of the months analyzed. The lowest efficiency scores occurred in April 2022 (63.2%), January 2023 (53.38%), and February 2023 (64.69%).

To facilitate a comprehensive understanding of the sector's efficiency trends throughout the analysis period and to support subsequent annual evaluations, annual efficiency figures were calculated and are presented in Table 6. From a managerial perspective, having access to these yearly values is essential for conducting high-level, rapid assessments of overall efficiency performance.

Table 6. Annual average efficiency.

Year	Annual Average Efficiency (%)
2018	97.95%
2019	96.11%
2020	97.78%
2021	93.70%
2022	75.90%
2023	75.90%
2024	99.40%
Mean	90.96%
Standard Deviation	10.44%
Median	96.11%

The variation in efficiency levels over the years may be attributed to both internal and external factors. For example, the COVID-19 pandemic led to a significant increase in demand for the company, which in turn caused a substantial reduction in the inventory of raw materials (input) and finished products (output) (Ivanov, 2020; Queiroz et al., 2022). Over the analysis period, the mean efficiency was 90.96%, the median was 96.11%, and the standard deviation was 10.44%.

To analyze targets and performance objectives, only inefficient DMUs were considered. Targets represent theoretical values that each output could reach while maintaining the same input level, aiming to improve the efficiency of the corresponding DMU (Charnes et al., 1978; Cooper et al., 2007). In the context of the DDF, the potential gain is defined as the difference between the observed input-output bundle and its projection onto the efficient frontier (Chung et al., 1997). Efficient DMUs, which followed best practices and made optimal use of inputs, were excluded from this analysis. Appendix C presents the targets and potential gains for the inefficient DMUs.

To illustrate the targets and gains derived from the model, the DMU for January 2022 is used as an example. During this period, 399 orders were released for production (desirable output), 10,656 thousand customer orders were not fulfilled within the expected timeframe (undesirable output), and personnel costs totaled BRL 178,000. If this DMU were operating efficiently, it would need to increase the number of released orders by 75 (gain), resulting in a target of 474. Concurrently, the number of late customer orders would need to be reduced by 2,013 thousand (gain), reaching a target of 8,642 thousand orders. Additionally, personnel costs could be reduced by BRL 33,651 thousand (gain), bringing the total down to BRL 144,349 thousand (target) for the period. As illustrated by the January 2022 DMU, the model aims to enhance desirable outputs while proportionally reducing undesirable outputs and inputs.

Translating these targets into managerial action requires identifying the operational factors associated with each variable. In the case of personnel costs, a reduction of the magnitude indicated for January 2022 may be pursued through adjustments in workforce scheduling, reduction of unplanned overtime, or reallocation of team members across concurrent activities, without necessarily implying headcount reduction. Regarding raw material inventory costs, the primary factor is the review of stock coverage parameters, that is, the number of days of supply held for each item, a decision directly linked to replenishment frequency and supplier lead times. Logistics costs, in turn, are sensitive to modal choices: shifting freight volume from air to road transport, where lead times permit, is typically the most impactful short-term action.

On the output side, increasing the volume of released orders generally depends on reducing internal bottlenecks in production scheduling, while decreasing unfulfilled orders requires improvements in demand forecasting accuracy and in the responsiveness of the replenishment process. The dashboard proposed in Section 4.2 supports this translation into managerial terms and helps prioritize actions based on their greatest potential gains.

4.2. Dashboard for monthly efficiency monitoring

The efficiency results presented in Section 4.1 serve as the quantitative foundation for the continuous monitoring dashboard described in this section. By systematically computing monthly efficiency scores, targets, and potential gains, the proposed model enables process managers to track performance trends and to support evidence-based decision-making on a recurring basis.

Figure 5 presents the cover page of the proposed dashboard for continuous efficiency monitoring. The dashboard is structured into five sections. The first section is the cover page of the report, followed by a summary of the topics addressed in each section, as shown in Table 7.

Table 7. Summary of dashboard sections.

Dashboard Section	Summary
Section 1: Cover Page	Cumulative efficiency chart for the past three years and monthly efficiency for the current year.
	Quick access to all other dashboard sections.
Section 2: Quarterly and Monthly Data	Chart 1: Quarterly efficiency data for a period defined by the analyst (e.g., Q1 2018 to Q2 2024).
	Chart 2: Annual efficiency values for a selected range (e.g., 2018 to 2023 and partial data for 2024).
Section 3: Target and Gain Analysis	Charts showing actual values, targets, and gains for each variable in the selected period.
	Notification regarding the shift or stability of the efficiency frontier
	Monthly efficiency information.
Section 4: Historical Inputs, Outputs, and Gains	Chart 1: Historical quarterly average values for each variable, with an option to select the variable to be analyzed.
	Chart 2: Historical quarterly average of potential gains if each DMU were efficient.
Section 5: Best Practice Mapping	Form for documenting and mapping best practices (RMBP) for months in which the efficiency frontier shifted.

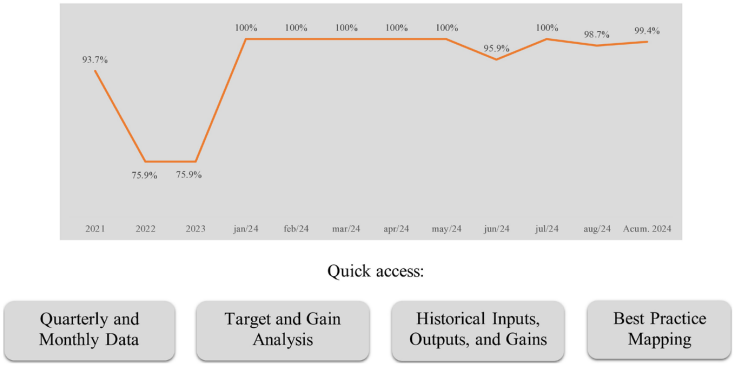


Figure 5. Cover page of the proposed dashboard.

The model was executed eight times to validate the proposed use of DEA as a continuous efficiency indicator and to better understand the model's behavior with the inclusion of new DMUs. In the first run, the model included 73 DMUs, covering the period from January 2018 to January 2024. Subsequently, input and output values for February were added, and the model was executed again. The efficiency score for February 2024 was incorporated into the dashboard, while the data for previous months remained unchanged from the January run. This process was repeated iteratively until efficiency scores, targets, and gains up to August 2024 were included. The results of this validation are shown in Table 8.

Table 8. Validation of DEA model behavior with the addition of new DMUs.

DMU	Result – Model Run Month by Month	August	July	June	May	April	March	February	January
01_2024	100.00%	83.50%	83.50%	83.50%	83.50%	83.50%	87.26%	87.81%	100%
02_2024	100.00%	95.74%	95.74%	95.74%	95.74%	98.24%	99.36%	100.00%	
03_2024	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
04_2024	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%			
05_2024	100.00%	100.00%	100.00%	100.00%	100.00%				
06_2024	95.91%	95.91%	95.91%	95.91%					
07_2024	100.00%	100.00%	100.00%						
08_2024	98.67%	98.67%							
Annual Average	99.3%	96.7%							

Based on the data presented in Table 8, it can be concluded that the efficient frontier of the model shifts only when a newly added DMU demonstrates higher efficiency than those previously included. This behavior is observed in February, March, April, and May. However, in June, when a DMU with lower efficiency was introduced, the efficiency values of the existing DMUs remained unchanged.

Therefore, the DEA efficiency frontier only shifts when a newly added DMU outperforms the existing ones. When a DMU with lower or equivalent efficiency is included, the frontier remains unchanged. This behavior is consistent with the mathematical properties of the DEA production frontier, which can only expand outward when a new observation presents a superior combination of inputs and outputs relative to existing reference points (Cooper et al., 2007).

Figure 6 illustrates this phenomenon. When a DMU with efficiency equal to or below the current frontier is added (cases A and B), the frontier remains unchanged (solid blue line). In contrast, if the new DMU surpasses the previously calculated frontier, the model updates the frontier (black dashed line), and the efficiency scores of

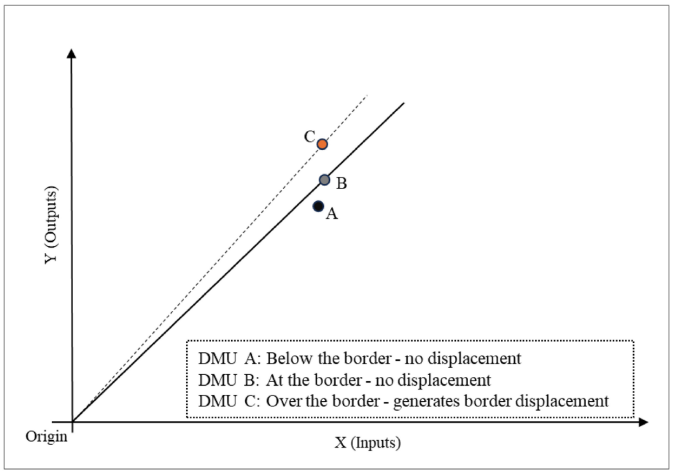


Figure 6. DEA frontier shift upon inclusion of a new DMU.

the previously efficient DMUs are recalculated. It is important to note that, throughout this study, the monthly efficiency values for 2024 were based on the *Result – Model Run Month by Month* column in Table 8.

A practical implication of this frontier behavior concerns how monthly targets should be interpreted for managerial purposes. Because the efficiency frontier can only expand outward as new DMUs are incorporated, a target calculated in each month reflects the best input-output combination observed up to that point in time. When a subsequent month introduces a more efficient DMU and the frontier shifts, previously calculated targets are updated to reflect the new benchmark. This does not invalidate past managerial decisions, rather, it indicates that a higher standard of performance has been observed and is now incorporated as the reference for efficiency calculations. Operationally, managers are recommended to use the most recent model run as the source of targets for planning purposes, since it represents the most demanding and most informed benchmark available. The iterative nature of the model is therefore a feature rather than a limitation: it ensures that the performance standard against which each month is evaluated evolves continuously as organizational knowledge accumulates.

A potential methodological concern raised is whether the frontier behavior observed reflects genuine efficiency differences or is an artifact of the limited number of variables included in the model. In DEA, having a limited number of inputs and outputs is actually necessary to preserve the discriminatory power of the model. When a model include a large number of variables relative to the number of observations, it suffers from a dimensionality problem, tending to assign full efficiency to a disproportionately large share of DMUs simply by default (Cooper et al., 2007).

To ensure that the frontier findings are robust and not a mathematical artifact, the standard rule of thumb is to apply the condition $n \geq \max(m \times s, 3(m + s))$, where n is the number of DMUs, m the number of inputs, and s the number of outputs (Cooper et al., 2007). In the present study, the model comprises three inputs and three outputs. Applying the rule yields a minimum requirement of 18 DMUs. Since our analysis utilizes 80 DMUs, the sample size greatly exceeds the minimum requirement, confirming that the model possesses strong discriminatory power and that the efficiencies observed reflect genuine performance differences. Furthermore, the selection of variables was not arbitrary: it followed five structured rounds of evaluation with internal and external experts, as described in Section 3.1, thereby reducing the risk that the model's results are driven by dimensionality effects rather than genuine operational performance differences.

It should be acknowledged, however, that the progressive incorporation of new DMUs constitutes an inherent methodological limitation of the proposed monitoring approach. As demonstrated in Table 8 and Figure 6, when a newly added DMU outperforms the existing frontier, efficiency scores for all previously evaluated months are retrospectively recalculated. This behavior is a structural property of the DEA production frontier and has been documented in the literature (Charnes et al., 1978; Cooper et al., 2007). In the present study, this limitation was partially mitigated through the dashboard architecture, which archives the efficiency values obtained at each model run and preserves historical records for managerial reference. Nevertheless, users of the proposed framework should be aware that the efficiency score reported for any given month may be subject to revision as subsequent high-performing DMUs are incorporated into the longitudinal analysis.

The third section of the dashboard was developed to provide process managers with detailed information on targets and potential gains for each month of the current year. For instance, it shows how much inputs should be reduced in a month when the sector was inefficient to reach efficiency, that is, the gain. It also shows the target, or the maximum value a DMU could achieve if it were efficient. The same analysis is available for desirable outputs, such as the number of released orders, indicating how much should be increased in each undesirable output to bring the sector to full efficiency. Figure 7 presents the dashboard using data from June 2024.

To assist managers in identifying when a frontier shift occurs, two types of alerts were implemented in the dashboard. In months such as June (Figure 7), where the frontier remains unchanged, the message "Frontier remained unchanged" is displayed. In contrast, in months when a new DMU outperforms previous ones, prompting a frontier shift, the alert " Attention: Frontier Shift" is shown.

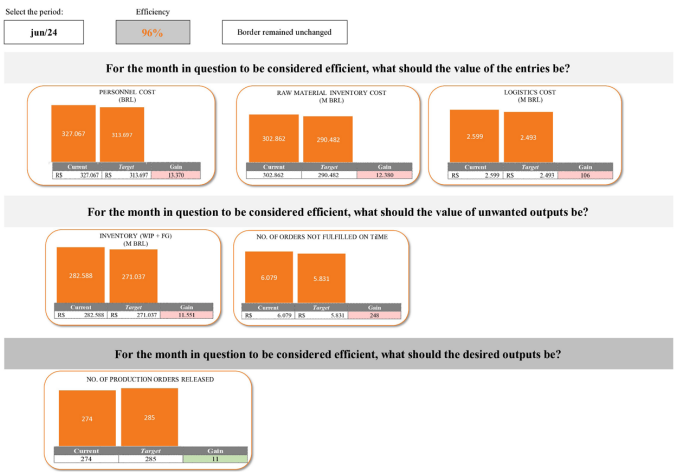


Figure 7. Period analysis.

The fourth section of the dashboard focuses on historical tracking and analysis of input and output values for each quarter from 2018 to 2023, as well as the months of 2024. This section also supports identifying the required increases in each variable to achieve higher efficiency levels in subsequent months. Figure 8 presents the graphs proposed for this section.

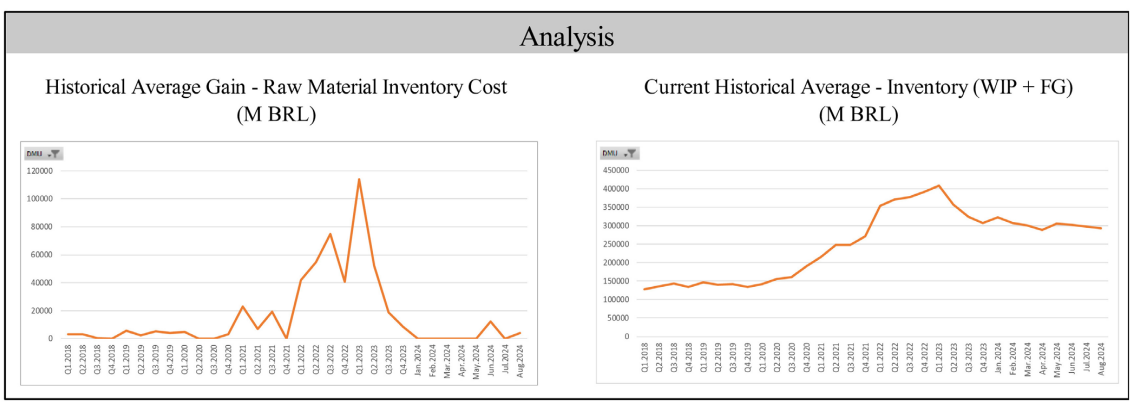


Figure 8. Historical average analysis.

To promote the replication of successful practices observed in a DMU in subsequent months and potentially incorporate them into the sector's standard procedures, a good practices mapping form was developed. A panel of experts contributed both to the creation of the form and to its validation.

The validation process focused on February 2024. In January, following new company guidelines and annual objectives, the parameters in the system were revised, with the understanding that lower inventory coverage levels could be adopted for some raw materials and semi-finished products. The analysis shows that the four months following these adjustments achieved 100% efficiency. Moreover, a continuous reduction was observed in both the input related to raw material inventory costs and the undesirable outputs, namely semi-finished and finished product inventories. This analysis was recorded in the dashboard, as shown in Table 9.

Table 9. Application of the good practices form.

Record Number	Description	Action	Follow-up Impact
R0001	Analysis covering the months of Feb/2024, Mar/2024, Apr/2024, and May/2024. The analysis involved the S&OP Analyst and the Supply Chain Manager. A consistent and gradual reduction in raw material and semi-finished product inventory levels was identified. This was attributed to stock coverage reviews and subsequent inventory reductions.	Increase the frequency of stock coverage evaluations for all items to a semiannual basis (at the time of the assessment, this review occurred only monthly). Monitor the sector's efficiency in the months following implementation.	4 months after changes

It is worth clarifying the timeline underlying this record. The operational changes in inventory coverage parameters were implemented in January 2024, following the annual strategic planning cycle. The resulting efficiency gains were observed during the subsequent four months (February through May 2024), all of which achieved 100% efficiency. The formal entry in the Good Practices Mapping Record (Table 9) bears the date of November 2024, which corresponds to when the documentation was completed after sufficient follow-up data had been collected to confirm the sustained impact of the intervention, not to when the operational changes were introduced.

Following the good practices mapping exercise conducted with the specialist team, the evidence gathered through the DEA analysis and the proposed dashboard revealed a recurrent pattern: efficiency gains in the materials planning area were consistently associated with deliberate changes in inventory coverage parameters, subsequently formalized through structured documentation. While this association was identified within a single longitudinal case and should be interpreted as observational rather than causal, it illustrates the analytical generalization potential of the proposed model.

The conceptual model presented in Figure 2 was designed to accommodate the structural characteristics common to production support areas, namely the coexistence of controllable inputs, desirable outputs, and undesirable outputs subject to operational constraints. By construction, the monitoring architecture is therefore intended to be adaptable to other support functions, such as maintenance planning, procurement, or quality control, by replacing the variables specific to materials planning with those governing efficiency in each respective area, while preserving the frontier shift detection mechanism, the target and gain analysis, and the good practices documentation structure. The design-level replicability of this architecture across different organizational contexts, rather than empirically demonstrated transfer, which remains to be validated in future studies, constitutes the analytical generalization contribution of the study, distinguishing the proposed framework from a context-bound empirical application.

5. Discussion of results

This study contributes to a deeper understanding of how to measure and continuously monitor the efficiency of support areas in production systems using DEA and internal benchmarking. The literature indicates both theoretical and practical interest in evaluating the efficiency of support areas (Abdeen et al., 2022; Alsyouf, 2006; Bianchi, 2012; Coenen et al., 2013; Ghosh et al., 2016; Kadam & Fonseca, 2009; Kristensen & Saabye, 2021; Mahmood & Mohd Zahari, 2021; Naji et al., 2022; Star et al., 2016). However, few empirical studies offer concrete methodologies for efficiency measurement, and even fewer address its longitudinal monitoring (a critical gap given the dynamic nature of production environments). Most existing approaches in performance evaluation rely on short-term financial indicators or isolated metrics that fail to capture interdependencies among variables (leading to local optimization and interdepartmental conflicts), nor do they enable systematic

longitudinal performance tracking (encouraging short-termism and failing to adapt as products and process move through their life cycles (Neely et al., 2005).

This research contributes to the literature by proposing a method for monthly efficiency tracking in production support areas. The findings demonstrate that DEA can serve as a recurring and dynamic efficiency indicator, representing, to the best of our knowledge, a novel approach in this context. An additional contribution is the empirical assessment of how the efficiency frontier shifts when new DMUs are incorporated into the model.

Such methodological contributions also have implications for benchmarking practice. When applied for internal benchmarking, the proposed monthly DEA framework enables systematic longitudinal assessment and the timely identification of persistent inefficiencies that may compromise business performance (Souza et al., 2018a). However, internal benchmarking inherently restricts comparison to the company's own historical observations and therefore does not substitute for evaluations against external or industry best practices (Piran et al., 2021). Consequently, the proposed approach should be positioned as a rigorous internal monitoring tool that complements periodic external benchmarking to ensure alignment with market performance standards.

In addition to presenting a conceptual framework, this research offers a practical application and a strategy for communicating efficiency metrics and performance across all organizational levels. It expands on the work of Kadam & Fonseca (2009), who focused on conceptual modeling, and Tornese et al. (2014), who employed consolidated theoretical methods with limited adaptability to specific industrial contexts.

Ghosh et al. (2016) proposed consolidating four KPIs into a single indicator via a dashboard. However, their model does not reveal the maximum attainable value for a specific KPI or identify which KPI would contribute most significantly to overall sector performance. The DEA-based efficiency analysis enabled a deeper understanding of which KPIs or outputs have the greatest impact on performance, as well as which adjustments are necessary to mitigate inefficiencies during the evaluation period.

This study contributes to the theoretical literature by demonstrating DEA as a suitable technique for recurring efficiency monitoring in support areas of production systems. The suitability of DEA for this purpose derives from its non-parametric nature, which requires no predefined functional form for the production frontier and therefore accommodates recurring application as new observations are incorporated over time (Charnes et al., 1978). The DDF extension is particularly appropriate in this context, as it simultaneously projects desirable outputs toward their maximum attainable values and undesirable outputs toward their minimum, producing a unified efficiency score that is directly comparable across periods (Chambers et al., 1996). The empirical results presented in this study demonstrate that monthly reapplication of the model produces interpretable and actionable efficiency trajectories, reinforcing its potential as an operational monitoring tool. It addresses existing gaps by enhancing prior research, such as Loch & Tapper (2002), who grouped 16 indicators into a single graph but did not explore their interactions, and Naji et al. (2022), who discussed 49 factors influencing support area performance but did not propose any consolidation approach.

A relevant methodological consideration concerns an inherent limitation of DEA models when new DMUs are incorporated over time: their insertion recalculates the efficiency frontier and may alter previously measured efficiency scores. In this study, this limitation was mitigated through the development of a dashboard that archived historical efficiency values, ensuring that scores from preceding periods remained unchanged upon the incorporation of new observations. This design decision preserves the integrity of the longitudinal analysis while making the recalculation mechanism transparent. Additionally, it is acknowledged that the findings regarding efficiency frontier shifts may be sensitive to the number of input and output variables included in the model. The variables adopted in this study were selected and validated through five rounds of expert evaluation, ensuring construct validity within the specific context investigated. Nevertheless, future studies incorporating a broader set of variables could further examine the robustness of the frontier behavior and contribute to the generalizability of the proposed framework.

Beyond theoretical contributions, this research also yields significant practical implications. There are also practical contributions for the company under study. The DEA analysis provided valuable insights into the sector's performance over time. Both specialists and management recognized the dashboard's potential in facilitating data-driven analysis and continuous improvement efforts. The collected data may support strategic planning and revision of operational standards and previous practices. Additionally, the company's specialists acknowledged the potential of extending DEA-based efficiency assessments to other support areas.

Currently, the company employs a broad set of indicators to evaluate various performance parameters. However, it does not assess the interdependencies among them or how changes in one may affect others. The DDF model allows these indicators to be aggregated into a single framework, enhancing the understanding of the relationship between inputs and outputs.

Finally, this research provides a foundation applicable to support areas of other production systems. The conceptual model used to define relevant inputs and outputs is not limited to the company studied. The generic structure of the conceptual model (Figure 2) can be systematically adapted to other support functions by following the same underlying logic: identifying department-specific deliverables as outputs, classifying them as desirable or undesirable according to their directional effect on organizational performance, and defining the controllable resources consumed to achieve those outputs as inputs. For instance, in a maintenance department, outputs could include equipment availability rates and preventive maintenance compliance rates (desirable) and unplanned downtime (undesirable), while inputs could encompass labor costs, spare parts expenditure, and maintenance service costs (Alsyouf, 2006). An information technology department could be evaluated using system availability, service request resolution time, and incident recurrence rates as outputs, with personnel and infrastructure costs as inputs. Similarly, a procurement department could adopt purchase order cycle time and supplier compliance rates as outputs and procurement personnel costs as inputs. In each case, the conceptual model developed in this study guides variable identification and operationalization, while the DEA-DDF framework provides the analytical mechanism for aggregating these variables into a single efficiency indicator. Also, the proposed dashboard and use of DEA as a recurring efficiency indicator can be replicated by other organizations seeking similar benefits. This suggests the analytical replication of the study's findings in other manufacturing and service companies.

6. Conclusion

This study aimed to develop an approach for longitudinal (i.e. tracking efficiency scores of the same DMUs across successive time periods) and continuous (i.e., enabling recurring and systematic assessments rather than isolated, one-time evaluations) efficiency monitoring in support areas of production systems. The model was implemented in a multinational company in the metal-mechanical sector, using a DDF combined with internal benchmarking.

The DDF model enabled simultaneous reduction of inputs and undesirable outputs while enhancing desirable outputs for inefficient DMUs. The first step was to define a conceptual model to support the identification of relevant inputs and outputs, making it applicable to any support area in production systems. Subsequently, the key variables for the selected area were identified, and the DEA model was applied. A dashboard was developed to present the efficiency results and to support longitudinal monitoring of sector performance.

The study contributes to the existing literature on continuous monitoring of support area efficiency. It shows that DEA can be used to calculate efficiency while considering multiple desirable and undesirable inputs and outputs. From a practical perspective, the information generated through DEA DDF modeling and the dashboard provides valuable insights for managers.

It is noteworthy that the conceptual model (e.g., Figure 2) allows for analytical generalization to other contexts. This conceptual model structure supports this transferability: at the first stage, inputs, desirable outputs, and undesirable outputs are defined at a conceptual level, applicable to any support area. At the second stage, an empirical model is derived for the specific context through iterative expert consultation. For instance, a maintenance area could adapt the model by mapping equipment availability and frequency of unplanned stoppages as key outputs, while a quality control area could consider inspection hours and defect rate as relevant variables. This adaptability reinforces the analytical generalization claim and extends the model's potential applicability beyond the materials planning context investigated here. However, the empirical model (e.g., Figure 3), derived from the conceptual model, was specifically applied to the analyzed case.

Nevertheless, despite efforts to include as many relevant variables as possible, DEA studies cannot guarantee the inclusion of all pertinent variables, as noted by Cook et al. (2014), representing a limitation of this study. Another limitation is that replicating the study requires redefining the model and mapping the relevant variables, thus requiring a new modeling process. A further methodological limitation concerns the incorporation of new DMUs over time: as new time periods are added to the analysis, the efficiency frontier is recalculated, which may revise previously obtained efficiency scores. In this study, this limitation was mitigated through the dashboard, which preserved archived efficiency scores from preceding periods and ensured that historical values remained stable and comparable across the monitoring horizon.

This research encourages further discussions on recurring efficiency monitoring in support areas and future studies applying DEA as a continuous performance indicator, regardless of the specific context.

Data availability

Research data is available in the body of the article.

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Appendix A. Systematic literature review protocol.

1. Overview

This appendix presents the full protocol of the Systematic Literature Review (SLR) conducted to identify and analyze studies on performance and efficiency evaluation in support areas of production systems. The SLR was carried out following a configurative review strategy and aimed to provide the theoretical foundation for the conceptual model developed in this study.

2. Search Protocol

Element	Definition / Choice
Research Question	How can Data Envelopment Analysis (DEA) be used to create a monthly efficiency indicator for a support area of a metal-mechanical industry?
Context	Development of a recurring indicator for the monthly efficiency assessment of a support area in a metal-mechanical company.
Time Horizon	Open (no restriction on publication year).
Languages	English and Portuguese.
Review Strategy	Configurative (synthesis oriented toward conceptual understanding and pattern identification, rather than statistical aggregation).
Search Sources	SCOPUS and EBSCOHost.
Search Fields	Title, Abstract, and Keywords.
Review Type	Peer-reviewed journal articles.

3. Eligibility Criteria

3.1 Inclusion Criteria

• Articles that used performance or efficiency indicators to evaluate support areas of companies in the metal-mechanical sector or analogous manufacturing contexts.

• Peer-reviewed articles written in English or Portuguese.

• Articles available for full-text download in the selected databases.

3.2 Exclusion Criteria

• Articles for which the full text was unavailable for download in the selected databases.

• Articles not written in English or Portuguese.

• Articles outside the scope of the research (i.e., not focused on performance or efficiency evaluation in organizational support functions).

• Studies not related to production systems for manufactured goods (e.g., purely service-sector or public-sector contexts with no connection to manufacturing operations).

4. Search Strings

EBSCOHost

TI ((“Key Performance Indicators” OR “Performance Metrics” OR “EFFICIENCY” OR “EFFECTIVENESS” OR “operational efficiency” OR “Organizational effectiveness” OR “Process Efficiency” OR “KPI” OR “Performance Efficiency”) AND (“Support Area” OR “Back Office” OR “Support Department” OR “Administrative Services” OR “Support Service” OR “Support Activities Areas” OR “Operational Support” OR “Support Functions” OR “Ancillary Areas” OR “Back-office” OR “Support Areas in Production Systems” OR “OPERATIONAL SUPPORT”))

SCOPUS

TITLE-ABS-KEY ((“Key Performance Indicators” OR “Performance Metrics” OR “EFFICIENCY” OR “EFFECTIVENESS” OR “operational efficiency” OR “Organizational effectiveness” OR “Process Efficiency” OR “KPI” OR “Performance Efficiency”) AND (“Support Area” OR “Back Office” OR “Support Department” OR “Administrative Services” OR “Support Service” OR “Support Activities Areas” OR “Operational Support” OR “Support Functions” OR “Ancillary Areas” OR “Back-office” OR “Support Areas in Production Systems” OR “OPERATIONAL SUPPORT”))

5. Search Results and Selection Procedure

The database searches were conducted in August 2024 and returned 2,368 records in total. After removing duplicates, 2,183 unique records were screened. The full selection procedure followed PRISMA guidelines and is illustrated in Figure A1 below.

Table A2. Search Results by Database

Database	Search Field	Records Retrieved	After Deduplication
EBSCOHost	Title	226	224
SCOPUS	Title, Abstract, Keywords	2,142	1,959
Total	–	**2,368**	**2,183**

Note: *Deduplication was performed using Rayyan reference management software.*

6. Article Selection Procedure

The article selection followed a four-stage procedure, consistent with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework:

Stage 1 – Identification: Database searches were conducted using the strings defined in Section 4. A total of 2,368 records were retrieved across EBSCOHost and SCOPUS.

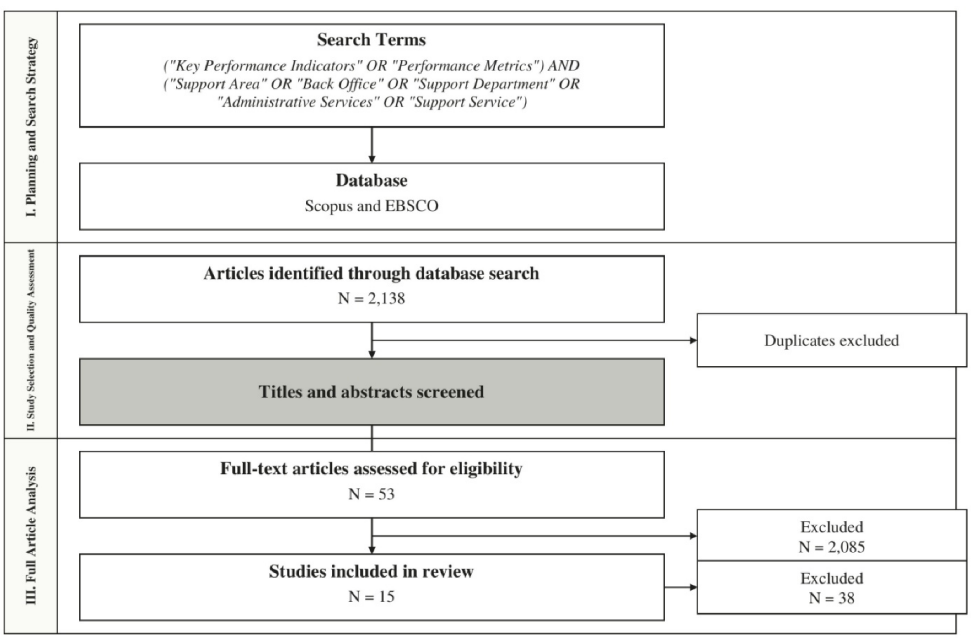
Stage 2 – Deduplication: Duplicate records were identified and removed, yielding 2,183 unique records for screening.

Stage 3 – Title and Abstract Screening: Records were screened by title and abstract against the inclusion and exclusion criteria defined in Section 3. Articles outside the scope of the research (those not related to performance or efficiency evaluation in support areas of manufacturing companies), not in English or Portuguese, or with full text unavailable, were excluded at this stage.

Stage 4 – Full-Text Eligibility Assessment: Remaining articles were retrieved and assessed in full text. Studies not related to production systems for manufactured goods were excluded. Articles addressing performance indicators and/or efficiency in support areas of manufacturing companies and reviewed by subject-matter experts were included in the final corpus.

The resulting set of articles published between 1995 and August 2024 formed the theoretical basis for the literature review presented in Section 2 of the main manuscript. The complete selection flowchart is presented in Figure A1.

7. Selection Flowchart



As shown in the flowchart, the search across the selected databases returned 2,368 records. After removing duplicates, applying language and availability filters, and excluding articles outside the research scope, the final corpus comprised the articles used to develop the theoretical background presented in Section 2 of this study.

Appendix B. Monthly technical efficiency.

DMU	Technical Efficiency (%)	DMU	Technical Efficiency (%)
Jan/18	91.12%	May/21	91.01%
Feb/18	94.86%	Jun/21	100.00%
Mar/18	100.00%	Jul/21	94.74%
Apr/18	98.11%	Aug/21	87.22%
May/18	100.00%	Sep/21	84.72%
Jun/18	91.83%	Oct/21	100.00%
Jul/18	100.00%	Nov/21	100.00%
Aug/18	100.00%	Dec/21	100.00%
Sep/18	99.46%	Jan/22	69.64%
Oct/18	100.00%	Feb/22	100.00%
Nov/18	100.00%	Mar/22	82.85%
Dec/18	100.00%	Apr/22	63.20%
Jan/19	84.05%	May/22	67.03%
Feb/19	97.76%	Jun/22	68.04%
Mar/19	100.00%	Jul/22	77.41%
Apr/19	100.00%	Aug/22	68.61%
May/19	100.00%	Sep/22	68.52%
Jun/19	95.01%	Oct/22	73.30%
Jul/19	91.66%	Nov/22	72.16%
Aug/19	100.00%	Dec/22	100.00%
Sep/19	96.07%	Jan/23	53.38%
Oct/19	97.84%	Feb/23	64.69%
Nov/19	100.00%	Mar/23	65.17%
Dec/19	90.98%	Apr/23	69.71%
Jan/20	88.55%	May/23	74.58%
Feb/20	95.79%	Jun/23	76.23%
Mar/20	98.03%	Jul/23	72.47%
Apr/20	100.00%	Aug/23	88.28%
May/20	100.00%	Sep/23	81.81%
Jun/20	100.00%	Oct/23	88.09%
Jul/20	100.00%	Nov/23	87.94%
Aug/20	100.00%	Dec/23	100.00%
Sep/20	100.00%	Jan/24	100.00%
Oct/20	100.00%	Feb/24	100.00%
Nov/20	94.87%	Mar/24	100.00%
Dec/20	96.16%	Apr/24	100.00%
Jan/21	80.51%	May/24	100.00%
Feb/21	100.00%	Jun/24	95.91%
Mar/21	86.15%	Jul/24	100.00%
Apr/21	100.00%	Aug/24	98.67%

Appendix C. Targets and gains for inefficient DMUs.

DMU	Personnel Cost (BRL)			Raw Material Inventory Cost (M BRL)			Logistics Cost (M BRL – air + road + maritime)			Released Orders			Inventory (WIP + FG)			Unfulfilled Orders		
	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)
01_2018	132.28	128.02	4.26	122.53	118.58	3.95	1.3	1.26	0.04	0.28	0.29	0.01	121.47	117.56	3.91	0.77	0.74	0.02
02_2018	148.71	142.74	5.96	127.72	122.6	5.12	1.43	1.38	0.06	0.31	0.33	0.01	119.04	114.27	4.77	1.59	1.53	0.06
04_2018	159.91	157.66	2.25	130.42	128.58	1.84	1.1	1.09	0.02	0.32	0.32	0	124.35	122.59	1.75	2.17	2.14	0.03
06_2018	158.45	149.55	8.9	142.18	134.19	7.99	1.23	1.16	0.07	0.34	0.36	0.02	148.86	140.5	8.37	0.87	0.82	0.05
09_2018	181.71	181.6	0.12	144.17	144.08	0.09	0.84	0.84	0	0.31	0.31	0	189.35	189.23	0.12	2.04	2.03	0.00
01_2019	138.48	124.26	14.21	150.16	134.75	15.41	1.33	1.2	0.14	0.24	0.26	0.02	168.14	150.88	17.25	1.52	1.36	0.16
02_2019	186.17	184.06	2.12	146.26	144.6	1.66	1.39	1.37	0.02	0.38	0.38	0	162.5	160.65	1.85	1.18	1.16	0.01
06_2019	164.87	156.73	8.14	136.9	130.14	6.76	1.13	1.07	0.06	0.33	0.34	0.02	180.9	171.97	8.93	0.61	0.58	0.03
07_2019	163.52	151.35	12.16	139.93	129.52	10.41	1.35	1.25	0.1	0.34	0.36	0.03	189.78	175.66	14.12	0.93	0.86	0.07
09_2019	172.68	165.89	6.79	142.46	136.86	5.6	1.33	1.28	0.05	0.33	0.35	0.01	206.69	198.57	8.12	0.67	0.64	0.03
10_2019	170.38	166.71	3.68	130.09	127.28	2.81	1.33	1.31	0.03	0.35	0.36	0.01	233.94	228.89	5.05	0.49	0.48	0.01
12_2019	147.01	136.99	10.02	139.27	129.78	9.49	0.81	0.75	0.06	0.25	0.26	0.02	242.65	226.12	16.54	0.96	0.9	0.07
01_2020	144.91	134.48	10.43	142.38	132.13	10.25	1.35	1.25	0.1	0.23	0.25	0.02	199.85	185.46	14.39	2.3	2.13	0.17
02_2020	171.58	166.16	5.43	137.44	133.09	4.35	1.09	1.05	0.03	0.32	0.33	0.01	190.21	184.19	6.01	3.06	2.97	0.10
11_2020	232.09	220.2	11.89	186.12	176.59	9.54	5.27	5	0.27	0.45	0.47	0.02	135.12	128.2	6.93	7.89	7.49	0.40
01_2021	183.12	149.42	33.7	207.88	169.62	38.26	6.3	5.14	1.16	0.42	0.5	0.08	128	104.45	23.56	9.24	7.54	1.70
03_2021	208.79	179.91	28.88	221.27	190.66	30.61	8.25	7.11	1.14	0.48	0.54	0.07	137.47	118.45	19.02	11.52	9.92	1.59
05_2021	228.06	208.89	19.17	244.76	224.19	20.57	7.97	7.3	0.67	0.45	0.49	0.04	143.08	131.05	12.03	10.84	9.93	0.91
07_2021	262.74	258.2	4.53	244.79	240.57	4.23	7.07	6.95	0.12	0.41	0.41	0.01	183.1	179.94	3.16	10.74	10.55	0.19
08_2021	231.78	212.98	18.8	250.08	229.8	20.28	6.34	5.83	0.51	0.38	0.41	0.03	225.27	207	18.27	9.84	9.04	0.80
09_2021	204.1	177.21	26.89	247.12	214.56	32.55	9.73	8.45	1.28	0.42	0.47	0.05	221.94	192.7	29.24	8.66	7.52	1.14
01_2022	178.06	144.41	33.65	335.77	272.31	63.46	11.28	9.15	2.13	0.4	0.47	0.08	227.79	184.74	43.05	10.66	8.64	2.01
03_2022	219.01	182.84	36.17	375.04	313.1	61.94	11.2	9.35	1.85	0.51	0.59	0.08	190.59	159.11	31.48	9.73	8.12	1.61
04_2022	202.77	161.89	40.88	375.84	300.07	75.77	7.19	5.74	1.45	0.45	0.54	0.09	208.89	166.78	42.11	8.99	7.18	1.81
05_2022	229.12	174.35	54.77	367.37	279.55	87.82	7.57	5.76	1.81	0.55	0.69	0.13	220.01	167.42	52.59	7.43	5.65	1.78
07_2022	286.25	258.6	27.65	375.63	339.35	36.28	7.24	6.54	0.7	0.51	0.56	0.05	270.96	244.79	26.17	7.94	7.17	0.77
08_2022	249.28	182.89	66.39	374.1	274.47	99.63	6.7	4.92	1.79	0.59	0.75	0.16	310.86	228.07	82.79	7.04	5.16	1.87
09_2022	227.8	175.13	52.67	381.05	292.95	88.1	8.38	6.45	1.94	0.48	0.59	0.11	335.59	258	77.59	4.56	3.51	1.05
10_2022	238.98	203.83	35.15	374.95	319.81	55.15	7.97	6.8	1.17	0.39	0.45	0.06	354.49	302.36	52.14	5.27	4.5	0.78
11_2022	244.92	201.4	43.52	377.23	310.2	67.03	6.92	5.69	1.23	0.44	0.51	0.08	386.8	318.07	68.73	4.34	3.57	0.77
01_2023	172.16	115.13	57.02	422.31	282.43	139.88	5.36	3.58	1.77	0.35	0.47	0.12	354.48	237.07	117.42	7.93	5.3	2.63
02_2023	235.47	180.25	55.21	412.51	315.78	96.73	3.56	2.72	0.83	0.41	0.51	0.1	380.93	291.61	89.33	5.25	4.02	1.23
03_2023	232.45	169.55	62.9	390.48	284.81	105.67	4.02	2.93	1.09	0.48	0.61	0.13	413.2	301.39	111.82	9.46	6.9	2.56

Appendix C. Continued...

DMU	Personnel Cost (BRL)			Raw Material Inventory Cost (M BRL)			Logistics Cost (M BRL – air + road + maritime)			Released Orders			Inventory (WIP + FG)			Unfulfilled Orders		
	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)	Value (thousand)	Target (thousand)	Gain (thousand)
04_2023	228.45	195.38	33.06	376.44	321.96	54.48	3.87	3.31	0.56	0.3	0.35	0.04	404.73	346.16	58.57	6.87	5.87	0.99
05_2023	247.53	217.02	30.52	356.09	312.19	43.9	3.62	3.17	0.45	0.34	0.39	0.04	428.68	375.83	52.85	4.35	3.81	0.54
06_2023	217.94	180.71	37.23	338.74	280.88	57.86	2.24	1.86	0.38	0.35	0.41	0.06	462.08	383.15	78.93	2.06	1.71	0.35
07_2023	212.25	192.88	19.37	334.8	304.24	30.55	2.79	2.53	0.25	0.23	0.25	0.02	449.89	408.83	41.06	4.57	4.15	0.42
08_2023	273.1	269.79	3.31	317.04	313.19	3.85	2.82	2.79	0.03	0.31	0.31	0	463.71	458.09	5.63	2.96	2.92	0.04
09_2023	234.03	218.06	15.97	320.76	298.87	21.89	2.04	1.9	0.14	0.27	0.29	0.02	450.88	420.12	30.77	2.53	2.36	0.17
10_2023	249.98	249.94	0.04	301.01	300.96	0.05	1.88	1.88	0	0.25	0.25	0	438.84	438.76	0.07	2.58	2.57	0.0004
11_2023	234.97	214.38	20.59	295.63	269.72	25.91	1.89	1.72	0.17	0.33	0.36	0.03	439.16	400.67	38.49	1.6	1.46	0.14
06_2024	327.07	313.7	13.37	302.86	290.48	12.38	2.6	2.49	0.11	0.27	0.29	0.01	282.59	271.04	11.55	6.08	5.83	0.25
08_2024	338.78	334.29	4.49	293.66	289.77	3.89	2.28	2.25	0.03	0.33	0.33	0	277.26	273.59	3.68	5.93	5.85	0.08