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Adaptive Performance Evaluation of Container Terminals Through Normalization and Parameter Analysis

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Abstract: *Background:* Container terminals are a pivotal part of global logistics networks, influencing supply chain reliability and port competitiveness. Traditional performance evaluation methods, such as KPI-based assessments or multi-criteria analyses, often fail in dynamic operational conditions with inherent uncertainty and variability. *Methods:* This study proposes a normalization-based framework to evaluate container terminal performance by standardizing operational parameters, including availability, non-productive operations, operation time, energy consumption, and throughput. The methodology involves parameter definition, normalization, weight assignment, index calculation, and performance classification. *Results:* The findings demonstrate that normalization ensures a transparent and adaptable evaluation framework. Sample calculations show how parameter weights influence terminal assessments across varied scenarios, confirming the robustness of the proposed method in capturing dynamic operational changes. *Conclusions:* Normalization offers a practical tool for enhancing container terminal efficiency and competitiveness. It enables decision-makers to adapt strategies to changing priorities, such as throughput maximization or energy efficiency, ensuring comprehensive and reliable performance assessments.

Keywords: container terminal performance; normalization-based evaluation; parametric evaluation

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1. Introduction

The efficiency of container terminals plays a crucial role in today's global logistics networks and supply chains, where there is a growing demand for reliable, high-throughput, and energy-efficient operations. The evaluation of terminal performance is based on complex criteria such as system availability, productivity, and environmental impact. Traditional assessment models often rely on deterministic and linear approaches, which may not fully account for the uncertainty and variability inherent in terminal operations, directly affecting the quality of their performance. The inability to dynamically adapt assessments to changing conditions, such as fluctuations in throughput or variations in the number of unproductive operations, leads to inaccurate results and may result in erroneous operational decisions.

To date, the performance evaluation of container terminals has most commonly utilized tools based on classical statistical methods and productivity indicators, such as Key Performance Indicators (KPIs) [1]. While these indicators are significant, they cover only selected operational aspects and are largely static, making them difficult to adapt to the dynamically changing work conditions of terminals. More advanced applications have included multi-criteria analysis methods, such as the Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA), which aid decision-making related to resource allocation and operational efficiency [2]. However, these methods require precise input data, and their effectiveness diminishes when data are characterized by high variability or lack of precision.

For instance, in cases of sudden increases in container traffic, deterministic performance indicators may fail to reflect rising downtime or increased energy consumption, leading to an incorrect assessment of the terminal's actual performance. Consequently, the terminal may be unable to identify operational bottlenecks early and optimize them, resulting in delays, increased operational costs, and a decline in the quality of services provided to clients. These limitations highlight the need for alternative methods that can effectively consider multiple parameters and inherent uncertainty.

A normalization-based approach has proven to be a robust and transparent method for evaluating container terminal performance. By scaling operational parameters to a common range, this approach ensures comparability and adaptability to dynamic changes in terminal conditions [3].

The article presents a resource allocation optimization model for automated container terminals, taking into account the dual-cycle operations of quay cranes. This model analyzes the operational system's efficiency and its asymptotic behavior under different resource allocation schedules, enabling increased terminal efficiency.

Meanwhile, in paper [4], a comparison is presented between static and dynamic performance parameters of major container terminals in China and Korea, utilizing a Super-SBM model based on slack variables and the Malmquist index method. The findings highlight the importance of normalizing operational parameters to ensure comparability and adaptability to dynamic changes in terminal conditions.

The article employs a hybrid multi-criteria approach, combining Principal Component Analysis (PCA) with the TOPSIS method, to evaluate and rank container terminals in Latin America and the Caribbean. The analysis included various operational variables such as quay length, depth, yard area, and the number of cranes, enabling the identification of criteria impacting the operational efficiency of terminals.

This publication highlights the importance of multi-criteria data analysis in evaluating and comparing container terminal performance, which is crucial for ensuring comparability and adaptability to dynamic changes in terminal operational conditions.

The objective of this study is to develop a container terminal performance evaluation model using a normalization-based framework, focusing on key operational factors such as availability, the number of unproductive operations, and energy efficiency. By integrating these variables into a single model, this study aims to provide a detailed evaluation method that overcomes the limitations of traditional assessment systems. The following research hypotheses are proposed:

"normalization ensures a consistent and transparent evaluation framework by standardizing operational parameters, enabling accurate performance assessments across varying operational scenarios."

2. Literature Review

The purpose of this literature review is to present existing research, methods, and models used in the evaluation of container terminal efficiency and to demonstrate how the application of fuzzy logic can enhance the process of operational assessment. This analysis includes tools used in container terminals, highlighting their limitations and applications in dynamically changing operational environments. The review is structured into several main sections, covering traditional and multi-criteria evaluation methods for container terminals and their limitations, the application of artificial intelligence in terminal assessment, and fuzzy logic as a decision-support tool.

Traditional and Multi-Criteria Methods for Evaluating Container Terminals

The evaluation of container terminals primarily relies on operational efficiency indicators known as Key Performance Indicators (KPIs), which include metrics such as average container handling time, equipment availability, and the number of operations per unit of time. KPIs serve as fundamental, easy-to-implement tools that provide a quick overview of a terminal's operational performance [5]. However, their main limitation is their static nature, which means they do not account for dynamic operational changes such as seasonal surges in container traffic or fluctuations in resource availability. Studies have shown that KPIs are useful in stable operational conditions but can lead to inaccurate assessments under high variability, which limits their value in more complex operational environments [6,7].

Article [8] reviews the latest methods for optimizing terminal operations, emphasizing traffic management efficiency and handling performance. This study indicates that standard KPIs, despite their widespread use, are often insufficient under dynamic operating conditions. The authors recommend integrated approaches that better account for seasonal traffic variations and resource variability, supporting decision-making processes. The article also suggests the development of more adaptive evaluation tools, including the use of predictive analytics.

In publication [9], the limitations of KPIs in assessing dynamic operational environments are analyzed. The authors critically examine traditional indicators, such as handling time and resource availability, arguing that they are static and fail to reflect operational fluctuations and seasonal demand peaks. The article contrasts earlier works [6,10], where KPIs were presented as sufficient performance measures under stable conditions.

More advanced cases of container terminal assessment employ multi-criteria analysis methods such as Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA). AHP allows for a hierarchical decomposition of problems into smaller criteria, which is particularly useful for strategic decision-making. DEA, on the other hand, enables the comparison of the performance of different units (e.g., container terminals) by evaluating efficiency based on input and output data, providing comprehensive results for unified performance assessments [10]. AHP is beneficial for the hierarchical assessment of strategic decisions in container terminals, supporting the evaluation and comparison of criteria essential for operational efficiency and resource management, such as equipment availability and port throughput [11]. DEA facilitates comparisons across multiple units, such as different terminals, allowing for the assessment of operational efficiency and resource allocation.

Research suggests that combining these methods, such as in a hybrid AHP-DEA model, offers a more flexible approach to multi-criteria evaluation, enabling more accurate assessments by leveraging the complementary features of both methods. AHP allows the assignment of weights to criteria, while DEA does not require prior assumptions regarding the relationships between inputs and outputs, making it advantageous in dynamic operational environments [8,12]. Furthermore, hybrid AHP-DEA approaches have proven effective in more complex analyses, such as the selection of transshipment ports, where various factors must be evaluated for their relative weight and importance [13].

Practical examples show that DEA is more effective when comparing multiple operational units with uniform data, while AHP supports decision-making in scenarios where qualitative assessment plays a crucial role. Ultimately, hybrid models like DEA-AHP can not only enhance the accuracy of assessments but also mitigate the limitations of using a single multi-criteria analysis method [14].

Traditional evaluation methods, while valuable under stable operational conditions, fall short in dynamic situations where operational parameters such as service time or the number of unproductive operations can fluctuate significantly. In rapidly developing container terminals, typical static approaches cannot keep pace with the need for flexibility and adaptation to changing conditions. For instance, when a terminal becomes more heavily loaded, traditional evaluation models do not provide adequate precision or accuracy in estimating actual operational performance, which can lead to ineffective resource allocation and capacity constraints [15,16].

In response to these challenges, more dynamic algorithms have been developed, such as the Monte Carlo-based container space allocation model, which optimizes terminal resource use and minimizes downtime [17]. Innovative approaches, including dynamic resource allocation algorithms, are essential to enhance efficiency and flexibility in highly variable operational conditions.

Despite their flexibility, dynamic algorithms encounter significant limitations. One major challenge is their high computational complexity, especially under large-scale operations, which can lead to prolonged processing times. Another limitation is their reliance on precise and up-to-date input data, which can be difficult to obtain in dynamic environments. The literature also highlights potential real-time optimization issues, limiting their effectiveness in rapidly changing operational conditions [16]. Dynamic algorithms used in container terminals, such as Ant Colony Optimization and machine learning-based models, present advanced solutions for resource allocation and scheduling but come with constraints. First, algorithms applied to berth allocation, for example, face challenges related to computational complexity, translating into long processing times for high-throughput terminals. An example is the Enhanced Ant Colony algorithm used for berth allocation, which improves efficiency but may require significant computational resources as the number of ships and containers increases [18]. Second, dynamic algorithms depend on accurate and current data, which is challenging to maintain in real operational environments. In automated terminals utilizing multi-vehicle systems (AGVs) and deep reinforcement learning for traffic management, the absence of precise data can lead to suboptimal decisions, reducing operational efficiency [19]. Another challenge is the need for adaptation to unforeseen events, such as vessel delays or equipment failures, which impact scheduling effectiveness and can result in increased downtime and inefficient resource use [20]. These challenges indicate the need for further development of dynamic algorithms to make them more resilient to variable operational conditions.

Application of Artificial Intelligence in Solving Operator Challenges

A new approach involves the application of artificial intelligence (AI) to solve challenges faced by container terminal operators. In [21], research on the optimization of automatic guided vehicle (AGV) routes using Q-learning is presented. It demonstrates how AI can be applied to reduce waiting times caused by vehicle interference on routes. The route matrix constructed with the Q-learning technique assists in planning optimal paths while considering the positioning of quay cranes.

Publication [22] introduces the OnPL (Online Preference Learning) algorithm, which allows for the dynamic adaptation of AGV task allocation policies to changing operational conditions. This algorithm employs a pairwise preference function, enabling the ranking and selection of the best tasks to minimize external vehicle waiting times at container terminals. OnPL ensures flexibility and efficiency in highly variable operational environments. In studies [18] on AGV scheduling in container terminals, various rules such as "first-come-first-serve" (FCFS), "shortest travel distance" (STD), and "longest waiting time" (LWT) were applied. Angeloudis and Bell's research showed that using a combination of different rules can improve scheduling performance more than applying a single rule.

This approach highlights that complex AI algorithms can address task allocation issues under the uncertainty and complexity of container terminals. Despite the benefits of AI, including flexibility and increased efficiency, the publication notes performance and learning efficiency problems as the complexity of the operational environment increases. A high number of variables and diverse operational conditions can elevate computational complexity, necessitating more sophisticated algorithmic solutions.

The literature review justifies the need for further research and development of evaluation methods that not only consider the specifics of dynamic operational conditions but also combine the flexibility of fuzzy tools with the precision of multi-criteria evaluation models. Summarizing the assessment methods for container terminals, it is evident that existing tools, such as KPIs, AHP, and DEA, although useful in stable operational conditions, have significant limitations in dynamic and variable environments. KPIs serve as basic metrics, but their static nature does not account for operational fluctuations and seasonal traffic surges, potentially leading to inaccurate performance evaluations under increased load conditions. In more advanced cases, multi-criteria analysis methods like AHP and DEA support strategic management and comparison of different terminals' efficiencies. While AHP facilitates the hierarchical evaluation of complex decisions and DEA is effective in analyzing operational efficiency, both methods require precise input data, which poses a challenge in dynamic conditions. Hybrid models, such as AHP-DEA, help overcome some of these limitations but are not free from difficulties related to data integration and real-time analysis constraints.

On the other hand, dynamic algorithms like Enhanced Ant Colony or multi-AGV systems using Deep Reinforcement Learning take a more flexible approach to operational assessment. Their limitations, including high computational complexity and dependence on current data, indicate that dynamic algorithms alone are not a universal solution. In this context, there is a justified need to seek more adaptive and integrated methods, such as fuzzy logic and Fuzzy TOPSIS, which better handle uncertainty and operational variability.

Application of Normalization as a Decision Support Tool

Normalization-based models are increasingly employed in risk analysis and operational efficiency evaluation for container terminals. Traditional risk assessment methods, which rely on classical statistical techniques, often struggle to address the dynamic and variable nature of terminal operations. Normalization offers a straightforward and transparent approach to standardizing operational data, enabling consistent and adaptable evaluation frameworks.

Examples in the literature highlight the use of normalization for evaluating and managing operational performance in container terminals. These models integrate various operational indicators, such as equipment availability, non-productive operations, and energy consumption, allowing for a holistic assessment of terminal efficiency. For instance, studies on seaport terminals have applied normalization techniques to standardize performance metrics and analyze their interdependence [23,24].

One of the primary advantages of normalization is its ability to simplify complex datasets by scaling parameters to a common range, typically [0, 1]. Unlike methods that require qualitative data or complex statistical assumptions, normalization provides a quantitative foundation that is both robust and easy to interpret. By normalizing variables such as "equipment availability" or "average energy consumption," terminal managers can perform scenario analyses that reflect current operational conditions. This flexibility allows normalization-based models to adapt to varying risk levels and operational priorities, making them highly suitable for decision-making in dynamic environments [25–28].

3. Method for Evaluating Container Terminal Performance Normalization

The objective of the research presented in this section is to propose a method for evaluating the performance of a container terminal using normalization as an analytical tool. This approach is chosen due to its ability to standardize diverse operational parameters, ensuring comparability and consistency in dynamic and complex environments where traditional evaluation methods, such as KPIs or multi-criteria analyses, may fall short.

This research aims to develop a model that enables a straightforward yet flexible assessment of various operational parameters, including process availability, handling time, energy consumption, energy efficiency, and the number of non-productive operations. The normalization process ensures that all parameters are scaled to a common range, typically [0, 1], allowing for the integration of diverse metrics into a unified evaluation framework.

First, the characteristics of the proposed normalization-based approach will be outlined, followed by an analysis of the mutual impact of individual parameters and their role in determining overall terminal performance.

3.1. Characteristics of the Proposed Method

The procedure for determining the parametric evaluation of a terminal comprises the following steps:

Step 1: Definition of performance parameters;
Step 2: Normalization of parameters;
Step 3: Assignment of weights to parameters;
Step 4: Calculation of the performance index (OPT);
Step 5: Classification of the evaluation.

A schematic representation of the method is shown in Figure 1.

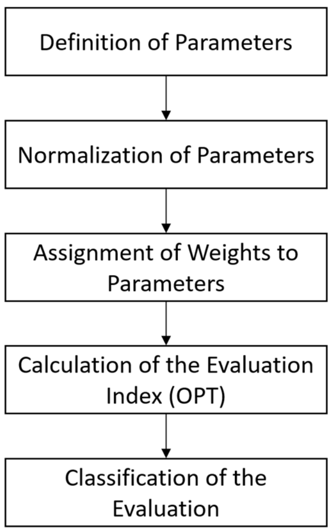

Figure 1. Schematic of the method implementation.

Step 1 involves defining the key performance parameters that will be used to analyze the functioning of the container terminal. This step requires identifying the most significant factors affecting operational efficiency, such as process quality, operational speed, and resource utilization. These parameters form the foundation for developing a comprehensive terminal evaluation method. Step 2 includes the normalization of the collected parameters to enable their comparison on a common scale ranging from 0 to 1. Normalization transforms raw data so that values fall within the same range. This allows for an easy assessment of how each parameter contributes to the overall terminal evaluation, which is essential for calculating the performance index. Step 3 involves assigning weights to the normalized parameters according to their importance in the terminal's evaluation. These weights reflect the priority of each parameter in the overall assessment, and their total sum must equal 1. Adjusting the weights enables customization of the evaluation method to meet the specific needs and priorities of a terminal, allowing for a flexible analysis of its operations. Step 4 entails the calculation of the performance index (OPT) based on the normalized parameters and their assigned weights. This index allows for the objective comparison of various operational scenarios and forms the basis for the final classification of terminal efficiency. The general solution for the method will be presented in the following section.

Step 1: Definition of Key Performance Parameters

Based on prior studies detailed in [29–31], the evaluation will be conducted using the following five parameters:

1. Availability (A)—measures the extent to which the terminal's equipment and systems operate without failure. This is a critical indicator that impacts operational continuity and minimizes downtime;
2. Number of Non-Productive Operations (NNO)—includes all activities that do not directly contribute to container handling, such as waiting for equipment availability or other delays. A high NNO indicates lower operational efficiency;
3. Operation Time (CTO)—refers to the average time taken to handle one container or a group of containers. Short operation times signify high efficiency;
4. Energy Consumption (ZE)—measures the amount of energy consumed during operations. Energy efficiency is important for operational cost management and sustainable development;
5. Throughput (P)—defined as the number of containers handled by the terminal within a specified time frame. High throughput indicates effective utilization of infrastructure and resources.

Detailed methods for determining these parameters are discussed in papers [32–35]. The definition of minimum and maximum values for each parameter based on operational data are as follows:

1. Availability factor (A)
   - Minimum value: $\mathrm{A_{min}}$
   - Maximum value: $\mathrm{A_{max}}$, *where* $\mathrm{A} \in [0,1]$
2. Number of Non-Productive Operations (NNO)
   - Minimum value: $\mathrm{NNO_{min}}$
   - Maximum value: $\mathrm{NNO_{max}}$, *where* $\mathrm{N} \in [0,\infty)$
3. Operation Time (CTO)
   - Minimum operation time (with travel): $\mathrm{CTO_{min}}$
   - Maximum operation time (with travel): $\mathrm{CTO_{max}}$, *where* $\mathrm{CTO} \in [0,\infty)$
4. Energy Consumption (ZE)
   - Minimum energy consumption: $\mathrm{ZE_{min}}$
   - Maximum energy consumption: $\mathrm{ZE_{max}}$, *where* $\mathrm{ZE} \in [0,\infty)$
5. Throughput (P)
   - Minimum throughput: $\mathrm{P_{min}}$
   - Maximum throughput: $\mathrm{P_{max}}$, *where* $\mathrm{P} \in [0,\infty)$

Step 2: Normalization of Parameters

Transformation of parameter values to a scale from 0 to 1 to enable comparison. The following normalization formulas are applied:

Availability (A):

$$A_{norm} = \mathrm{A} \tag{1}$$

Availability is an indicator that takes values within the range [0, 1], as it is defined as the ratio of operational time to total time (including both operational and downtime). Consequently, it does not require additional normalization in the evaluation model, simplifying calculations and enhancing methodological clarity. From a probabilistic perspective, as a function representing the likelihood that a system is in a state of readiness at any given time, this indicator also falls within the same [0, 1] range, maintaining consistency with fundamental principles of probability theory.

Number of Non-Productive Operations (NNO):

$$NNO_{norm} = 1 - \frac{NNO - NNO_{min}}{NNO_{max} - NNO_{min}} \tag{2}$$

Operation Time (CTO):

$$CTO_{norm} = 1 - \frac{CTO - CTO_{min}}{CTO_{max} - CTO_{min}} \tag{3}$$

Energy Consumption (ZE):

$$ZE_{norm} = 1 - \frac{ZE - ZEO_{min}}{ZEO_{max} - ZEO_{min}} \tag{4}$$

Throughput (P):

$$P_{norm} = \frac{P - P_{min}}{P_{max} - P_{min}} \tag{5}$$

Step 3: Assignment of Weights to Parameters

Assign a weight (w_i) to each parameter such that the total sum of weights equals 1. The parameter weights are as follows:

- Availability (R): w_R,
- Number of Non-Productive Operations (NNO): w_{NNO},
- Operation Time (CTO): w_{CTO},
- Energy Consumption (ZE): w_{ZE},
- Throughput (P): w_P.

The weights assigned to the parameters w_R, w_{NNO}, w_{CTO}, w_{ZE}, w_P are determined by terminal management and reflect the specific priorities and strategic goals of the terminal. These priorities vary depending on the operational context and the objectives that the terminal seeks to achieve. For example, if high productivity is the primary goal, the weight assigned to energy consumption w_{ZE} might be relatively low, as energy efficiency is less critical in this scenario. Conversely, if minimizing the number of non-productive operations w_{NNO} is the main focus, throughput w_P might be assigned a lower weight as it becomes a secondary concern.

This flexibility in assigning weights allows the evaluation model to adapt to different strategic needs. For instance, a terminal with operational characteristics optimized for low energy consumption might receive a low OPT value if productivity is prioritized, as its parameters are less aligned with this goal. However, under the same operational conditions, the same terminal would achieve a high OPT value if energy efficiency were the primary priority. Therefore, the assignment of parameter weights is specific to each strategy and reflects the terminal's objectives, ensuring the model's adaptability and relevance in varying operational contexts.

Step 4: Calculation of the Terminal Performance Index (OPT)

The overall terminal performance index can be calculated using the following formula:

$$OPT = w_R \times R_{norm} + w_{NNO} \times NNO_{norm} + w_{CTO} \times CTO_{norm} + w_P \times P_{norm} \tag{6}$$

Step 5: Classification of Terminal Performance

Classify the terminal's performance based on the OPT value, dividing it into four categories: unacceptable, average, satisfactory, and good.

Definition of Thresholds:

Assume three threshold values a, b, and c, where:

$$0 < a < b < c < 1$$

The classification can be defined as follows:

- Unacceptable: OPT∈[0, a)
- Average: OPT∈[a, b)
- Satisfactory: OPT∈[b, c)
- Good: OPT∈[c, 1].

The boundary values for the intervals (a, b, c) in the classification of the OPT indicator were designed as general parameters that can be adapted to specific industry requirements or empirical results. The values aa, bb, and cc are decisive boundaries, and a given OPT value belongs to the lowest category if OPT < a and transitions to the next higher category when OPT = a.

The interval boundaries should align with operational performance standards recognized in logistics or container terminal management. For example, terminals with an OPT value below aa may be classified as "insufficient" in terms of efficiency, whereas those above cc meet the highest performance standards. This approach enables the boundary values to be grounded in existing guidelines or best practices within the industry.

Another method for determining boundary values involves analyzing the operational performance results of terminals in a specific region or group of terminals. Using historical data allows the boundaries to be adjusted to natural efficiency thresholds, such as distinct differences in performance between terminals with low and high levels of productivity. In this article, the values adopted are similar to those presented in articles [32–35].

3.2. Preliminary Calculation Example

This section presents sample calculations using the proposed method.

Definition of linguistic variables:

1. Availability (R)
   - Low: below 95%
   - Medium: 95% to 98%
   - High: above 98%
2. Number of Non-Productive Operations (NNO)
   - Low: fewer than 4
   - Medium: 4 to 7
   - High: 8 and above
3. Operation Time (CTO)
   - Operation time depends on the container layer, influencing the duration evaluation.

These dependencies are shown in Table 1.

Table 1. Linguistic variables for operation time.

Layer	Short [s]	Medium [s]	Long [s]
1	< 40	40–60	>60
2	< 50	50–80	>80
3	< 80	80–150	>150
4	< 150	150–240	>240

4. Energy Consumption (ZE) (hourly consumption)
    - Low: less than 15 L/hour
    - Medium: 15–20 L/hour
    - High: above 20 L/hour

    Considering Distance:

    - Short distance: less than 30 m
    - Medium distance: 30–150 m
    - Long distance: over 150 m
5. Throughput (P)
    - Low: fewer than 20 cycles/hour
    - Medium: 20–35 cycles/hour
    - High: above 35 cycles/hour

Parameter weights
The following weights are assumed:

- Availability (R): 0.3
- Number of Non-Productive Operations (NNO): 0.2
- Operation Time (CTO): 0.2
- Energy Consumption (ZE): 0.1
- Throughput (P): 0.2

Total weights: 0.3 + 0.2 + 0.2 + 0.1 + 0.2 = 1
Calculation of the Overall Performance Index (OPT)
The overall terminal performance index is calculated using Formula (6):

$$OPT = w_r \times R_{norm} + w_{NNO} \times NNO_{norm} + w_{CTO} \times CTO_{norm} + w_P \times P_{norm}$$

Classification of Terminal Performance
Performance classification can be defined with the following ranges:

- Good: OPT > 0.8
- Satisfactory: 0.6 < OPT $\leq$ 0.8
- Average: 0.4 < OPT $\leq$ 0.6
- Unacceptable: OPT $\leq$ 0.4

Assumptions for calculations:

- Availability (R): 97%
- Number of Non-Productive Operations (NNO): 5
- Operation Time (CTO): 70 s (Layer 2)
- Energy Consumption (ZE): 18 L/hour
- Throughput (P): 30 cycles/hour

Normalization of Parameters (Based on Assumed Limits):

- Availability (R):

$$R_{norm} = \frac{0.97 - 0.9}{1 - 0.9} = \frac{0.07}{0.1} = 0.7$$

- Number of Non-Productive Operations (NNO):

$$NNO_{norm} = 1 - \frac{5 - 0}{10 - 0} = 0.5$$

- Energy Consumption (ZE):

$$ZE_{norm} = 1 - \frac{18 - 10}{25 - 10} = 1 - \frac{8}{15} \approx 0.467$$

- Throughput (P):

$$P_{norm} = \frac{30 - 15}{50 - 15} \approx 0.429$$

Calculation of OPT:

$$\text{OPT} = (0.3 \times 0.7) + (0.2 \times 0.5) + (0.2 \times 0.5) + (0.1 \times 0.467) + (0.2 \times 0.429) = 0.5415$$

Classification:
Since $0.4 < \text{OPT} < 0.6$, the terminal performance evaluation is classified as "average".

3.3. Analysis of Inter-Parameter Influence and Method Modification

The parameters used for evaluating container terminal performance are highly interrelated, and their interactions significantly influence the overall efficiency. For example, reduced Availability leads to higher Non-Productive Operations (NNO), longer Operation Time (CTO), and increased Energy Consumption (ZE), ultimately lowering Throughput (P). Similarly, high NNO not only extends CTO but also increases ZE and reduces P. These interdependencies underscore the necessity of balancing parameters based on specific strategic priorities, such as maximizing productivity or minimizing energy consumption.

To account for these interactions, parameter weights w_R, w_{NNO}, w_{CTO}, w_{ZE}, w_P are dynamically adjusted according to the terminal's operational goals. This dynamic approach ensures that the evaluation framework remains adaptable and relevant under varying operational conditions.

Mathematical relationships between parameters
(a) Relationship Between NNO and CTO
Assume a direct linear or non-linear relationship between the number of non-productive operations and the operation time:

$$CTO = CTO_{prod} + NNO \times t_{nprod} \tag{7}$$

where:

- CTO_{prod}—productive operation time,
- t_{nprod}—average time per non-productive operation.

(b) Relationship Between CTO and ZE
Energy consumption is proportional to operation time:

$$ZE = P_{moc} \times CTO \tag{8}$$

where:

- $\mathrm{P_{moc}}$—average power used during operations (constant or variable).

(c) Relationship Between CTO and P

Throughput is inversely proportional to operation time:

$$P = \frac{3600}{CTO} \tag{9}$$

where:

- 3600—number of seconds in an hour,
- CTO—average time for one operation in seconds.

(d) Relationship Between R and NNO

Lower Availability may lead to more non-productive operations:

$$NNO = NNO_{base} + k \times (1 - R) \tag{10}$$

where:

- NNO_{base}—base number of non-productive operations at ideal Availability,
- k—proportionality constant.

Model Modifications

(a) Combining CTO and ZE

Since ZE depends on CTO, the weight for CTO can be adjusted to reflect its impact on energy consumption:

$$w'_{CTO} = w_{CTO} + w_{ZE} \tag{11}$$

(b) Combining NNO and CTO

If NNO affects CTO, a cumulative operation time parameter can be created:

$$CTO_{cumulative} = CTO + NNO \times t_{nprod} \tag{12}$$

Taking into account the above dependencies, a simplified model with three main parameters can be presented:

- Availability (R)
- Cumulative Operation Time ($CTO_{cumulative}$)
- Throughput (P)

$$OPT = w_r \times R_{norm} + w_{CTO} \times CTO_{norm} + w_P \times P_{norm} \tag{13}$$

where CTO_{norm} is the normalized cumulative operation time.

Considering these parameter relationships allows for a more realistic evaluation of terminal performance. Reducing the number of parameters through the inclusion of interdependencies simplifies the model and can increase its clarity. Mathematical relationships between parameters can be used to predict the impact of changes in one parameter on others, which is valuable for decision-making processes.

The final OPT value can vary based on the selected weights and the values of the individual parameters. Table 2 presents a set of equations characterizing possible forms of the OPT equation as a function of w_R, under the following scenarios:

(1) w_R decreases, w_{CTO} increases, w_P is constant,
(2) w_R decreases, w_P increases, w_{CTO} is constant,
(3) w_{CTO} decreases, w_R increases, w_P is constant,
(4) w_{CTO} decreases, w_P increases, w_R is constant,
(5) w_P decreases, w_R increases, w_{CTO} jest is constant,
(6) w_P decreases, w_{CTO} increases, w_R is constant.

Table 2. Set of OPT equations based on w_R in assumed scenarios.

Scenario	Equation OPT(w_R)	Coefficient a_i	Coefficient b_i
1	$OPT(w_r) = a_1 w_r + b_1$	$a_1 = k_{CTO} CTO_{norm}$	$b_1 = OPT_{start} - a_1 w_{Rstart}$
2	$OPT(w_r) = a_2 w_r + b_2$	$a_2 = k_P P_{norm}$	$b_2 = OPT_{start} - a_2 w_{Rstart}$
3	$OPT(w_r) = a_3 w_r + b_3$	$a_3 = k_R R_{norm}$	$b_3 = OPT_{start} - a_3 w_{Rstart}$
4	$OPT(w_r) = a_4 w_r + b_4$	$a_4 = k_P P_{norm} - k_{CTO} CTO_{norm}$	$b_4 = OPT_{start} - a_4 w_{Rstart}$
5	$OPT(w_r) = a_5 w_r + b_5$	$a_5 = k_R R_{norm} + k_P P_{norm}$	$b_5 = OPT_{start} - a_5 w_{Rstart}$
6	$OPT(w_r) = a_6 w_r + b_6$	$a_6 = k_{ZE} ZE_{norm} + k_{CTO} CTO_{norm}$	$b_6 = OPT_{start} - a_6 w_{Rstart}$

Calculating b_i involves determining the initial value of OPT at a given w_R.

4. Analysis of the Proposed Method: Achieved OPT Values and Operational Priorities

Adopting different priorities, such as emphasizing high throughput instead of availability, can lead to different assessments of terminal performance. Changing the weights assigned to individual parameters in the evaluation model impacts which aspects of terminal operations are highlighted. As a result, a terminal can receive a higher or lower assessment depending on whether the priority is throughput or availability.

Priority on Availability

An availability-focused approach is crucial when handling hazardous or sensitive goods, such as chemicals, explosives, pharmaceuticals, or medical equipment. In such cases, minimizing the risk of equipment or system failures that could lead to accidents, environmental contamination, or loss of valuable goods is paramount. High availability ensures the safety of workers, the environment, and cargo while also meeting legal and insurance requirements.

Another example of prioritizing availability is during the fulfillment of contracts with key clients who demand high-quality service and availability. Maintaining high availability is essential for customer satisfaction, avoiding contractual penalties, and sustaining long-term business relationships. High availability builds the terminal's reputation as a trustworthy partner and ensures smooth operations within the broader supply chain, where delays or failures can significantly impact the entire logistics network. Ensuring uninterrupted operations is critical for maintaining supply chain fluidity and minimizing delays and additional costs.

Priority on Operation Time

Operation time is a priority when handling perishable goods such as food, flowers, or other products with a short shelf life. Quick handling is necessary to maintain product quality and ensure timely delivery. Reducing operation time minimizes the risk of product spoilage and customer dissatisfaction.

An example of this priority is maintaining strict schedules, where delays can cause knock-on effects at other transfer points (e.g., ports). Fast handling reduces ship port stays, which saves costs for shipowners and maintains schedules, potentially making the terminal more appealing for future operations. Additionally, fast operations are essential during peak traffic periods (e.g., pre-holiday seasons) when the terminal must handle more containers in a short period. Effective time management increases terminal throughput during critical periods, preventing congestion and delays.

Priority on Throughput

Throughput becomes a priority when the terminal handles large shipping lines requiring the processing of significant container volumes in a short timeframe. Increasing the number of handled cycles per hour is essential to meet customer demands. High throughput enables the handling of more ships and increases the terminal's revenue.

When a terminal competes with others in the region, demonstrating high efficiency and the ability to manage large volumes can attract new clients. Additionally, when a terminal has invested in modern equipment and infrastructure capable of handling higher container volumes, maximizing operational capacity helps achieve a return on investment. High throughput translates to increased revenue and cost efficiency.

Balanced Weights—A Comprehensive Approach

Aside from emphasizing specific strategies, a balanced approach is also viable. This is often seen in the implementation of long-term sustainable development strategies, where a terminal aims to maintain a stable market position through balanced management of all operational aspects. Equal weighting of availability, operation time, and throughput is beneficial when serving diverse clients with varying needs and expectations, allowing for flexible adaptation to individual client requirements and fostering long-term business relationships and loyalty.

Balanced weighting can also support terminal operations aimed at continuous process optimization by focusing on all key performance indicators (KPIs). This improves overall terminal performance and competitiveness.

Scenario analysis of weight changes

The assumptions for the calculations remain the same as in Section 3.2:

- Availability R = 0.95
- Cumulative Operation Time $CTO_{cumulative}$ = 120 s
- Throughput P = 30 cycles/hour

OPT calculations were conducted for the following scenarios:

1. w_R = 0.6 decreases to 0.2, w_{CTO} increases from 0.2 to 0.6, w_P remains constant at 0.3,
2. w_R = 0.6 decreases to 0.2, w_P increases from 0.2 to 0.6, w_{CTO} r remains constant at 0.3,
3. w_{CTO} = 0.6 decreases to 0.2, w_R increases from 0.2 to 0.6, w_P remains constant at 0.3,
4. w_{CTO} = 0.6 decreases to 0.2, w_P increases from 0.2 to 0.6, w_R remains constant at 0.3,
5. w_P = 0.6 decreases to 0.2, w_R increases from 0.2 to 0.6, w_{CTO} remains constant at 0.3,
6. w_P = 0.6 decreases to 0.2, w_{CTO} increases from 0.2 to 0.6, w_R remains constant at 0.3.

Table 3 presents the results for the first scenario.

Table 3. OPT calculation results for scenario 1.

w_R	w_{CTO}	w_P	OPT
0.6	0.2	0.2	0.5545
0.55	0.25	0.2	0.5659
0.5	0.3	0.2	0.5773
0.45	0.35	0.2	0.5886
0.4	0.4	0.2	0.6
0.35	0.45	0.2	0.6114
0.3	0.5	0.2	0.6227
0.25	0.55	0.2	0.6341
0.2	0.6	0.2	0.6455

It can be observed that reducing the priority of availability while increasing the weight of operation time leads to an increase in the terminal's evaluation. The function for this scenario is $\mathrm{OPT}(w_R) = -0.2273(w_R) + 0.6909$. Table 4 shows the OPT functions for each scenario.

Table 4. OPT function parameters for each scenario.

Scenario	Function $\mathbf{OPT}(w_R)$	OPT for $w_R = 0.6$	OPT for $w_R = 0.2$
1	$\mathrm{OPT}(w_R) = -0.2273 \cdot w_R + 0.6909$	0.5545	0.6455
2	$\mathrm{OPT}(w_R) = -0.0455 \cdot w_R + 0.6091$	0.5819	0.6
3	$\mathrm{OPT}(w_R) = 0.2273 \cdot w_R + 0.4182$	0.5545	0.5637
4	$\mathrm{OPT}(w_R) = -0.2273 \cdot w_R + 0.7818$	0.6455	0.7364
5	$\mathrm{OPT}(w_R) = -0.0455 \cdot w_R + 0.5818$	0.5545	0.5727
6	$\mathrm{OPT}(w_R) = -0.1818 \cdot w_R + 0.6818$	0.5727	0.6091

From the functions and initial and final results, the influence of changing parameter weights on terminal evaluation can be analyzed.

In scenario 3, where availability is clearly dominant, increasing the weight of availability w_R leads to a significant rise in the OPT value. This demonstrates that availability has a dominant impact on the terminal's assessment when it is prioritized, while the weights of other parameters, such as throughput w_P, remain constant. The operation time CTO is crucial in scenarios where its weight increases, indicating its fundamental role in terminal efficiency. A high weight assigned to operation time directly translates into a better assessment of the terminal's performance, suggesting that reducing the time required to carry out operations is a priority for optimization. Time efficiency is a vital operational indicator because it enables faster container handling, minimizes bottlenecks, and increases overall throughput. In practice, this means that terminals capable of optimizing operation execution time gain competitiveness and better meet the requirements of customers and shipowners. Faster operations also contribute to increased customer satisfaction and improved cargo turnover rates.

Examining the results for scenario 1, it can be observed that decreasing the weight of availability w_R and simultaneously increasing the weight of operation time w_{CTO} leads to an increase in the OPT value. This indicates that operation time plays a key role in the terminal's assessment in this scenario. Similarly, in scenario 6, increasing the weight of operation time while decreasing the weight of throughput w_P also leads to a rise in OPT, underscoring the importance of time efficiency in operational processes. Availability is a significant factor influencing the assessment, especially in scenarios where its weight increases. Although its impact on the assessment is evident, it often yields to the significance of operation time. Operational stability and minimization of failures are crucial for ensuring the smooth functioning of the terminal, particularly when handling valuable or sensitive goods and when collaborating with demanding clients. High availability translates into reduced operational risk and increased certainty of operations, which is strategically important for long-term contracts and maintaining a positive image of the terminal. However, in situations where speed and dynamism of handling are critical, availability may give way to the importance of time efficiency.

Throughput is the dominant parameter in scenarios 4 and 2. In the former, decreasing the weight of operation time w_{CTO} and increasing the weight of throughput w_P indicates the growing significance of the ability to handle a larger number of containers. Throughput becomes an essential parameter when the key goal is to maximize the operational efficiency of the terminal and increase revenues by handling large cargo volumes. For scenario 2, changes in OPT are moderate; increasing the weight of throughput while decreasing the weight of availability shows that the terminal may prefer the ability to quickly handle large quantities of cargo, which can be crucial in a competitive market environment, especially during peak traffic periods. Throughput affects the terminal's assessment, but its importance is more moderate compared to availability and operation time. While high throughput denotes the terminal's ability to handle more containers per unit of time—which is beneficial for increasing revenues and operational efficiency—its impact on the performance assessment is less if other key parameters, such as availability and operation time, are not at adequately high levels. Throughput reflects more the terminal's capacity to process large volumes in a short time, which may be less critical in scenarios requiring greater precision and availability. Nevertheless, with an appropriate balance with other parameters, it can serve as a factor supporting the improvement of the assessment, especially in the context of maximizing the financial and operational efficiency of the terminal.

Each of these scenarios highlights how changing the weights of parameters affects the overall assessment of the terminal, allowing for the adjustment of operational strategies to evolving priorities and business requirements.

The chosen method, based on normalization, provides a straightforward and transparent framework for evaluating container terminal performance. By scaling all parameters to a common range [0, 1] the method ensures comparability and eliminates the need for subjective definitions, such as membership functions in fuzzy logic. However, normalization has its limitations.

One challenge is the reliance on predefined parameter ranges, which may need periodic updating to reflect changes in operational conditions or technological advancements. Additionally, normalization treats all parameters independently, which may not fully capture complex interdependencies unless addressed through weight adjustments or scenario-based analysis. Despite these limitations, normalization remains a robust and adaptable tool, particularly in contexts where simplicity and clarity are critical.

5. Conclusions

The normalization-based approach offers significant practical advantages in container terminal management. First, it enables real-time performance monitoring by providing a unified metric for evaluating key operational parameters. This makes it easier for decision-makers to identify areas requiring improvement, such as reducing Non-Productive Operations (NNO) or optimizing Energy Consumption (ZE).

Additionally, the method supports strategic planning by allowing the flexible adjustment of parameter weights to reflect changing priorities, such as increasing throughput during high-demand periods or reducing energy costs during off-peak times. Unlike methods that rely on qualitative assessments, normalization offers a quantitative foundation that is easily interpretable and comparable across different scenarios. This makes it particularly valuable for applications like capital allocation, site selection, and stakeholder collaboration, where transparent and consistent evaluation is essential.

The calculation examples and the analysis of parameter weight impacts confirmed the model's effectiveness in reflecting real working conditions, especially in dynamic and variable environments. The model allows for the identification of areas that require improvement and enables a faster response to changing operational conditions.

The developed methodology was validated through scenario simulations, which assessed its practical applicability. The analysis of parameter weight impacts revealed that prioritizing different operational aspects leads to varied assessment results. Notably, it was highlighted that operation time has a dominant influence on the final assessment when its weight increases, whereas Availability plays a crucial role in contexts requiring stability and risk minimization. Throughput, while important, was found to have a lesser impact compared to other parameters unless it is prioritized. The results confirm that a fuzzy logic-based approach is effective in modeling complex operational environments, allowing for flexible adaptation of the evaluation to changing conditions. The presented solutions can serve as a foundation for strategic and operational decision-making in container terminals.

Future work includes extending the model to incorporate additional variables and integrating artificial intelligence algorithms to more accurately represent terminal operational complexity. The development of real-time decision-support tools based on dynamic fuzzy logic models could further contribute to increased terminal efficiency and operational flexibility.

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