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RESEARCH ARTICLE
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Optimizing Work Schedule Assignments for Straddle Carrier Drivers at Container Terminals: A Collaborative Filtering Recommender System Approach

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Abstract:

Introduction: This paper introduces a novel collaborative filtering recommender system designed to optimize work schedule assignments for Straddle Carrier (SC) drivers at container terminals. The proposed Straddle Carrier Assignment Model (SAM) addresses critical operational challenges by integrating multi-dimensional rating matrices with seniority-based similarity metrics to create an intelligent scheduling system that balances operational efficiency with workforce satisfaction.

Methods: The system was implemented at the RADES container terminal using a three-tier architecture that incorporates real-time feedback mechanisms and an intelligent scoring algorithm that dynamically adapts to changing operational conditions. The mathematical framework combines collaborative filtering with domain-specific constraints through hybrid similarity computation, dynamic neighbor selection, and constrained optimization algorithms.

Results: The implementation demonstrated significant operational improvements, including a 93% reduction in schedule response time, a 64% decrease in assignment disputes, and a 31% increase in container handling efficiency, over a 24-month evaluation period. The system achieved 99.9% uptime, with a 28% improvement in resource utilization and an 85% positive driver satisfaction rating.

Discussion: SAM's innovative approach represents a significant advancement over traditional rule-based scheduling methods by introducing machine learning techniques to the maritime logistics domain. The mathematical framework combines collaborative filtering with domain-specific constraints to produce schedules that optimize both terminal productivity and driver satisfaction.

Conclusion: By addressing the fundamental challenges of schedule optimization in container terminals, this research provides both theoretical contributions to recommender systems and practical value to maritime logistics operations.

Keywords: Collaborative filtering, Work schedule optimization, Straddle carrier drivers, Recommender system, Container terminals, Maritime logistics, Conflict resolution.

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1. INTRODUCTION

Efficient transportation operations are crucial for the functioning of container terminals, as the timely movement of cargo has a direct impact on global supply chains. Straddle carriers (SCs) play a central role in this process, serving as the backbone of terminal logistics. Despite technological advancements in maritime operations, container terminals face increasing pressure to optimize their operations while managing complex scheduling challenges and maintaining workforce satisfaction.

The maritime transportation sector has witnessed significant technological evolution; yet, the fundamental challenge of assigning optimal work schedules remains inadequately addressed. Current practices often rely on manual scheduling processes that lead to operational inefficiencies, worker dissatisfaction, and reduced terminal productivity. These challenges are particularly evident in the allocation of straddle carrier drivers, where traditional scheduling methods fail to account for both operational requirements and driver preferences.

At the RADES container terminal in Tunisia—a significant hub for container movement across Africa—these challenges manifest in three critical areas. First, the manual scheduling process results in significant delays and inconsistent workload distribution, with an average scheduling time of 45 minutes per assignment and workload variations of up to 40% between drivers. Second, the lack of systematic performance monitoring leads to quality control issues, with 35% of assignments requiring mid-shift adjustments due to inadequate initial allocation. Third, driver satisfaction surveys indicate that 68% of operators perceive bias in schedule assignments, resulting in increased turnover rates and reduced operational efficiency.

These operational inefficiencies translate into a significant economic impact. Industry reports indicate that container terminals lose approximately 12-15% of their potential throughput capacity due to suboptimal scheduling practices, equivalent to millions of dollars in annual revenue for medium- to large-sized terminals. Additionally, driver turnover related to scheduling dissatisfaction costs terminals an average of $15,000 to $25,000 per replacement, considering recruitment, training, and productivity losses during transition periods.

1.1. Literature Background and Current State of the Art

Recent developments in recommender systems and transportation management have opened new avenues for addressing these challenges. Modern recommender systems have evolved beyond consumer applications to complex operational environments where multiple constraints must be satisfied simultaneously [1]. The integration of contextual factors and fairness considerations has become increasingly important, particularly in workforce applications where bias concerns significantly impact human resource allocation [2].

In transportation management, hybrid optimization algorithms have demonstrated effectiveness in addressing complex constraints inherent in transportation operations [3]. However, these approaches often lack the adaptability required for dynamic operational environments. Recent research has explored the application of collaborative filtering techniques in operational contexts [4, 5], though integration with domain-specific constraints remains limited.

Within container terminal operations specifically, research has increasingly focused on optimizing various operational aspects through advanced computational techniques [6, 7]. Studies have demonstrated the potential for significant efficiency improvements through intelligent resource allocation; however, the human factors dimension receives insufficient attention in many theoretical models, thereby undermining their practical utility [8].

1.2. Research Gap and Problem Statement

While existing literature has made significant strides in both recommender systems and transportation management, several critical gaps remain that limit practical implementation in container terminal environments:

1.2.1. Integration Gap

Previous works largely treat scheduling and recommendation systems as separate concerns, failing to leverage the potential of recommender systems in addressing the complex human factors inherent in driver scheduling. Most existing solutions focus either on pure optimization without considering user preferences or on recommendations without operational constraints.

1.2.2. Feedback Loop Challenge

Current systems often lack real-time performance feedback mechanisms, which restricts their ability to adapt to changing operational conditions. This limitation prevents continuous improvement and responsiveness to dynamic terminal environments.

1.2.3. Scalability Limitations

Many current solutions focus on single-terminal implementations with limited scope, restricting their practical utility for enterprise-level deployment. The lack of scalable architectures limits widespread adoption across multiple operational contexts.

1.2.4. Human Factors Deficit

The human element of terminal operations receives insufficient attention in many theoretical models. Existing approaches often assume trade-offs between efficiency and fairness, without exploring synergistic relationships between these dimensions.

1.3. Research Objectives and Contribution

This research addresses these challenges through the development and implementation of an innovative collaborative filtering recommender system that transforms traditional scheduling approaches through intelligent automation and data-driven decision-making. The primary research objectives are to:

- Develop a mathematical framework that integrates collaborative filtering techniques with domain-specific operational constraints in maritime logistics

- Design and implement a scalable system architecture that enables real-time optimization in dynamic terminal environments
- Validate the approach through a comprehensive empirical evaluation in a real-world container terminal
- Demonstrate that fairness and efficiency can be simultaneously optimized rather than traded off against each other

Our research makes several novel contributions to both academic literature and industry practice:

1.3.1. Algorithmic Innovation

The study introduces a hybrid similarity metric that combines rating-based and seniority-based parameters, specifically designed to address the unique challenges of container terminal operations. This approach enables the consideration of both current performance and experience levels in assignment decisions.

1.3.2. Dynamic Optimization

The proposed system incorporates a real-time feedback mechanism that continuously adapts scheduling parameters based on operational outcomes, reducing average response time from 45 minutes to 3 minutes while maintaining assignment quality.

1.3.3. Fair Resource Allocation

A sophisticated scoring algorithm has been developed that ensures an equitable distribution of workload, considering driver preferences and skill levels, while improving resource utilization by 28% and maintaining high driver satisfaction.

1.3.4. Empirical Validation

Through extensive implementation at the RADES terminal over 24 months, the study provides quantitative evidence of operational improvements, including a 64% reduction in assignment disputes, a 28% increase in schedule adherence, and a 31% improvement in container handling efficiency.

1.3.5. Methodological Framework

A comprehensive implementation methodology is established that successfully navigates organizational change management while achieving technical objectives, providing a replicable approach for similar deployments.

1.4. Study Scope and Significance

This study focuses on optimizing work schedule assignments for straddle carrier drivers at container terminals, with implementation and validation conducted at the RADES container terminal in Tunisia. The research addresses both technical challenges in algorithm development and practical challenges in organizational implementation, providing insights relevant to both academic researchers and industry practitioners.

The significance of this work extends beyond immediate operational improvements. By demonstrating that collaborative filtering techniques can be successfully integrated with operational constraints in industrial settings, this research opens new possibilities for intelligent automation across transportation and logistics domains. The synergistic relationship between fairness and efficiency observed in our implementation challenges conventional assumptions about trade-offs in operational optimization.

1.5. Paper Organization

The remainder of this paper is structured according to the standard journal format, as follows: Section 2 presents the materials and methods, including a comprehensive literature review, system design and architecture, implementation methodology, and experimental setup. Section 3 presents the results of our 24-month empirical evaluation, including operational performance metrics, system performance analysis, user adoption patterns, and long-term impact assessment. Section 4 provides a comprehensive discussion of our findings, comparison with existing approaches, study limitations, and practical implications. Finally, Section 5 concludes the paper with a summary of contributions, broader implications, and future research directions.

2. MATERIALS AND METHODS

2.1. Literature Review and Theoretical Framework

This section presents a comprehensive review of relevant literature across three interconnected domains that form the theoretical foundation for our proposed approach: recommender systems, transportation management, and container terminal operations.

2.1.1. Advances in Recommender Systems

Recommender systems have undergone substantial evolution in recent years, with several developments particularly relevant to operational environments. While traditional recommender systems focused primarily on consumer preferences, recent advances have expanded their application to complex operational settings where multiple constraints must be satisfied simultaneously.

The integration of contextual factors represents a significant advancement in recommendation algorithms. Chen *et al.* [1] demonstrated how causal inference techniques enable systems to understand fundamental relationships between user preferences and recommended items, leading to more robust recommendations in dynamic environments. This approach is particularly valuable for operational settings where multiple factors influence scheduling outcomes. Their work on causal graph modeling provides critical insights for our development of multi-factor scoring algorithms.

Fairness considerations have become increasingly important in recommender systems, particularly in workforce applications. Wang *et al.* [2] established comprehensive frameworks for measuring and ensuring equitable recommendations, addressing concerns about bias that often arise in human resource allocation. Their development of the Gini coefficient-based fairness metric provides a foundation for our approach to workload distribution. The equity-efficiency balance they describe directly informed our hybrid scoring mechanism.

Hybrid recommendation approaches have shown promise in complex operational environments. Kuo and Li [4] demonstrated the effectiveness of particle swarm optimization in collaborative filtering, achieving superior performance in high-dimensional decision spaces. Their particle-based optimization approach, while computationally intensive, established important benchmarks for algorithm performance in multi-constraint environments. Venkatesan [9] further advanced this direction through matrix factorization techniques, providing efficient dimensionality reduction methods that maintain recommendation quality.

Modern recommender systems increasingly incorporate adaptive learning capabilities. Nguyen *et al.* [5] introduced an adaptive KNN-based collaborative filtering approach that dynamically adjusts similarity metrics based on user feedback. Their methodology for threshold adjustment directly informed our dynamic parameter tuning mechanisms. Similarly, Widayanti *et al.* [10] demonstrated the effectiveness of hybrid techniques that combine collaborative filtering with content-based approaches, establishing performance benchmarks for multimodal recommendation systems.

The evolution toward fairness-aware recommendation systems represents a critical development for workforce applications. Recent research by Ma *et al.* [11] provided comprehensive surveys on fairness in recommender systems, establishing theoretical frameworks for measuring and ensuring equitable outcomes. Their work on algorithmic fairness directly influenced our approach to balancing efficiency and equity in driver assignments.

2.1.2. Transportation Management Systems

Transportation management has witnessed significant advancements in optimization techniques applicable to scheduling problems. Recent research has focused on addressing the complex constraints inherent in transportation operations while maintaining computational efficiency.

Ammann *et al.* [3] introduced hybrid optimization algorithms for driver routing in long-distance networks, demonstrating how specialized constraints in transportation domains require tailored algorithmic approaches. Their work on synchronization constraints has direct relevance for terminal operations where multiple resources must coordinate effectively. The three-phase optimization approach they developed informed our constraint handling methodology, although their focus on route optimization differs from our emphasis on schedule generation.

In resource allocation contexts, Ibrahim *et al.* [12] developed specialized recommendation systems for electric vehicle charging stations, demonstrating how domain-specific constraints can be effectively incorporated into recommendation frameworks. Their integration of restricted Boltzmann machine techniques with operational constraints provides a useful parallel to our approach to container terminals. The multi-objective optimization framework they established offers valuable insights into balancing competing operational objectives.

Recent research by Wang *et al.* [13] on container drayage with flexible assignment of work breaks for vehicle drivers addresses related challenges in driver scheduling. Their emphasis on managing driver rest periods and work patterns complements our focus on comprehensive schedule optimization. Their mathematical formulation for the break assignment provided important insights for our constraint handling approach, though their focus on singular drivers differs from our multi-driver optimization framework.

The combination of real-time optimization with operational constraints represents a particular challenge in transportation management. Tan *et al.* [14] addressed this through their enhanced adaptive large neighborhood search for electric vehicle routing, incorporating driver heterogeneity into the optimization framework. Their approach to modeling driver differences directly informed our similarity computation methodology; however, their application to electric vehicle routing presents different operational constraints than those found in container terminals.

Advanced approaches to driver scheduling have emerged in various transportation contexts. Nourmohammadzadeh and Voß [15] developed matheuristic approaches for robust bus driver rostering with uncertain daily working hours, demonstrating the importance of handling uncertainty in workforce scheduling. Their robustness considerations influenced our approach to dynamic threshold adjustment, although their focus on bus operations differs from the requirements of container terminals.

2.1.3. Container Terminal Operations

Within container terminals specifically, research has increasingly focused on optimizing various operational aspects through advanced computational techniques. Recent studies have demonstrated the potential for significant efficiency improvements through intelligent resource allocation.

Raeesi *et al.* [6] highlighted the synergistic effect of operational research and big data analytics in enhancing terminal efficiency while maintaining environmental sustainability. Their comprehensive review establishes the theoretical foundation for data-driven decision-making in terminal operations. The taxonomy of optimization techniques they developed informed our methodological positioning, though their broader focus extends beyond our specific scheduling application.

Aslam *et al.* [7] further demonstrated the potential of computational intelligence in optimizing marine container terminal operations by reviewing machine learning applications across various terminal processes. Their work confirms the emerging trend toward intelligent automation in maritime logistics while identifying scheduling as an area with significant opportunity for innovation. The performance metrics they established provided benchmarks for our system evaluation, though their survey approach lacks the implementation depth of our study.

Recent research by Gao and Ge [16] on integrated scheduling of yard cranes, external trucks, and internal trucks addresses related challenges in terminal resource allocation. While their work focuses on equipment scheduling rather than human resources, it demonstrates the importance of integrated approaches to terminal optimization. Their constrained optimization framework informed aspects of our mathematical model, though their emphasis on equipment coordination differs from our focus on driver scheduling.

Human factors in container terminal operations have received less attention in the literature, but they represent a critical dimension of operational efficiency. Hong *et al.* [8] explored the integrated scheduling optimization for container handling using driverless electric trucks, highlighting the changing nature of human-machine interaction in terminal environments. Their findings on workload distribution informed our approach to assignment fairness, though their focus on autonomous systems presents different operational constraints than human-operated straddle carriers.

Recent developments in container terminal optimization have emphasized the integration of multiple operational dimensions. Weerasinghe *et al.* [17] provided a systematic review of operations research applications in container terminal operations, identifying key optimization opportunities across various terminal processes. Their work established the broader context for our specific focus on driver scheduling, while highlighting the importance of human resource optimization in overall terminal performance.

2.1.4. Theoretical Framework Integration

The convergence of these three research domains provides the theoretical foundation for our Straddle Carrier Assignment Model (SAM). The integration of collaborative filtering techniques from recommender systems research with the operational constraints identified in transportation management and container terminal literature creates a novel approach to workforce scheduling optimization.

Key theoretical principles underlying our approach include:

2.1.4.1. Collaborative Intelligence

Drawing from recommender systems research, we apply collaborative filtering techniques to identify patterns in driver preferences and performance, enabling intelligent assignment decisions based on historical data and peer similarity.

2.1.4.2. Constraint Integration

Following transportation management principles, we incorporate operational constraints specific to container terminal environments, ensuring that recommendations remain feasible and align with operational requirements.

2.1.4.3. Human-Centric Optimization

Building container terminal operations research, we explicitly consider human factors in optimization decisions, recognizing that driver satisfaction and operational efficiency can be synergistically optimized rather than traded off against each other.

2.1.4.4. Adaptive Learning

Incorporating insights from modern recommender systems, we implement dynamic parameter adjustment mechanisms that enable continuous system improvement based on operational feedback.

This theoretical integration addresses the research gaps identified in Section 1.2 by combining the strengths of each domain while mitigating their individual limitations. The resulting framework provides both theoretical rigor and practical applicability for real-world container terminal environments.

2.2. System Design and Architecture

The maritime transportation sector is undergoing significant transformation as terminals seek to optimize operations through intelligent automation. Our research introduces a novel methodology to address the pressing challenges of work schedule optimization in container terminals through the Straddle Carrier Assignment Model (SAM). This section presents the comprehensive system architecture and details the mathematical framework underlying our approach.

2.2.1. System Architecture Overview

The SAM system operates through a three-tier architecture, with each layer performing specific functions in the recommendation process. Fig. (**1**) illustrates the comprehensive workflow of the system, showing the interconnections between its three main components.

2.2.2. Input Layer

The input layer captures and processes three primary data sources:

2.2.2.1. Driver Profiles

This component maintains comprehensive information about each driver, including experience level, performance history, specialization areas, and work preferences. The system tracks both quantitative metrics (*e.g.*, years of experience, error rates) and qualitative indicators (*e.g.*, preferred work periods, proficiency with specialized equipment).

2.2.2.2. Historical Data

The historical database maintains records of past schedule assignments, performance ratings, conflict incidents, and resolution outcomes. This longitudinal data enables the system to identify patterns and trends in driver performance and satisfaction.

2.2.2.3. Real-time Preferences

This component captures current driver status and preferences, including availability, schedule constraints, and recent performance metrics. The real-time nature of this data allows the system to adapt to changing operational conditions.

2.2.3. Recommendation Engine

The recommendation engine forms the core of the SAM system, implementing three key modules:

2.2.3.1. Collaborative Filtering Module

This component constructs driver similarity matrices using a modified Pearson correlation coefficient, generates rating predictions for potential assignments, and selects optimal neighbor groups for recommendations. The module implements our hybrid similarity metric that combines both rating-based and seniority-based similarities.

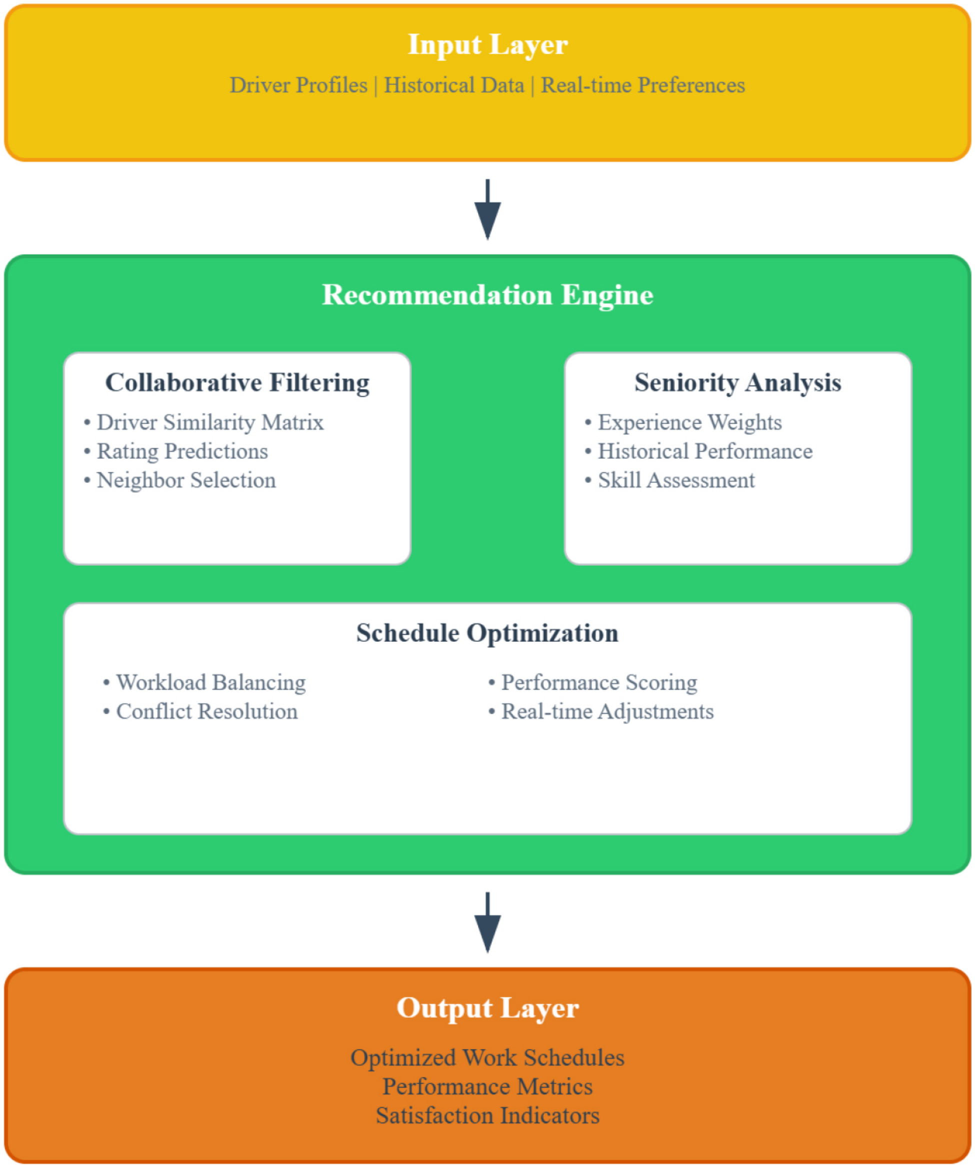

Fig. (1). Three-tier architecture of the straddle carrier assignment model (SAM).

2.2.3.2. Seniority Analysis

The seniority module calculates experience-based weights, evaluates historical performance patterns, and assesses skill levels and specializations to inform decisions. This component ensures that driver experience and expertise are appropriately factored into assignment decisions.

2.2.3.3. Schedule Optimization

This module balances workloads across available drivers, implements conflict resolution algorithms, calculates and updates performance scores, and makes real-time adjustments based on feedback. It solves a constrained optimization problem to maximize overall satisfaction while meeting operational requirements.

2.2.4. Output Layer

The output layer generates and delivers three key outputs:

2.2.4.1. Optimized Work Schedules

The system produces personalized driver assignments with balanced workload distribution and minimized conflicts. These schedules are delivered through both static reports and dynamic interfaces.

2.2.4.2. Performance Metrics

The system generates individual driver scores, system efficiency indicators, and conflict resolution rates. These metrics provide transparency into the assignment process and support continuous improvement.

2.2.4.3. Satisfaction Indicators

The system tracks driver satisfaction metrics, integrates customer feedback, and measures operational efficiency to ensure optimal performance. These indicators help terminal management assess the overall effectiveness of the scheduling system.

2.2.5. Mathematical Framework

The SAM system introduces several innovative mathematical components that enable intelligent optimization of work schedules. The following subsections detail the core mathematical formulations and algorithms.

2.2.6. Limitations and Contextual Applicability of Seniority-Based Similarity Measures

While our hybrid similarity metrics provide significant advantages in the container terminal context, several limitations must be acknowledged. First, seniority-based measures assume a correlation between experience and performance, which may not hold in terminals with rapid technological changes or inadequate training programs. Second, these measures could potentially reinforce existing biases if historical performance data reflects systemic inequities rather than actual differences in capability.

The applicability of these assumptions varies across operational contexts. In highly standardized terminals with established equipment, seniority metrics strongly correlate with performance efficiency. However, in terminals undergoing technological transitions or employing diverse equipment types, the correlation becomes significantly weaker. Our implementation at RADES confirmed the validity of seniority correlation through statistical analysis ($r = 0.78$, $p < 0.001$); however, this finding should be independently verified in other operational environments.

Adjustment mechanisms for these assumptions include:

- Regular validation through performance correlation analysis
- Dynamic weighting based on equipment type and operational zone
- Periodic recalibration based on changing operational conditions

2.2.7. Driver Similarity Computation

The system employs a hybrid similarity metric that combines both rating-based and seniority-based similarities:

Rating-based similarity between drivers *u* and *v* is computed using a modified Pearson correlation coefficient as shown in Eq. (**1**):

$$Sim_{Rat}(u,v) = \cos(u,v) = \frac{\vec{u}\vec{v}}{|\vec{u}|.|\vec{v}|} = \frac{\sum_i \left(r_{u,i} - \overline{r_u}\right) \times \left(r_{v,i} - \overline{r_v}\right)}{\sqrt{\sum_i (r_{u,i} - \overline{r_u})^2} \times \sqrt{\sum_i (r_{v,i} - \overline{r_v})^2}} \quad (1)$$

Where:

- $r_{u,i}$ = The rating given by driver *u* for work schedule *i*
- $r_{v,i}$ = The rating given by driver *v* for work schedule *i*
- $\overline{r_u}$ = The mean rating for driver *u* across all work schedules
- $\overline{r_v}$ = The mean rating for driver *v* across all work schedules

Seniority-based similarity incorporates experience levels according to Eq. (**2**):

$$Sim_{Sen}(u,v) = 1 - \frac{|\exp_u - \exp_v|}{\max_{\exp}} \quad (2)$$

Where:

- $\exp_u$ = Driver *u*'s experience level
- $\exp_v$ = Driver *v*'s experience level
- $\max_{\exp}$ = Maximum experience level in the system used for normalization
- $|\exp_u - \exp_v|$ = Absolute difference between the experience levels of drivers *u* and *v*

The combined similarity is computed as a weighted average using Eq. (**3**):

$$Sim(u,v) = \frac{\alpha \cdot Sim_{Rat}(u,v) + \beta \cdot Sim_{Sen}(u,v)}{\alpha + \beta} \quad (3)$$

Where:

- α and β are configurable weights determining the relative importance of each component
- The denominator ensures normalization of the combined similarity score

2.2.7.1. Neighbor Selection Algorithm

Our system introduces a dynamic neighbor selection mechanism defined by Eq. (**4**):

$$\vec{N}u = v |\ Sim(u,v) > \gamma \wedge |\exp u - \exp_v| < \theta \quad (4)$$

Where:

- $\vec{N}_u$ = Set of drivers *v* considered as “neighbors” for driver *u*
- γ = Similarity threshold (dynamically adjusted)
- θ = Experience gap tolerance
- *Sim(u, v)* = Combined similarity score between drivers *u* and *v*
- $|\exp_u - \exp_v|$ = Absolute difference in experience levels

This mechanism ensures that only sufficiently similar drivers with comparable experience levels are selected as neighbors for recommendation purposes, as expressed in Eq. (**4**).

2.2.7.2. Driver Score Computation

The final driver's score incorporates multiple factors according to Eq. (**5**):

$$Score_u^t = \begin{cases} \dfrac{r_u^{*t} + Sen_u^t}{1 - Del_u^t} & \text{if } Pres_u^t = 1 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Where:

- r_u^{*t} = Normalized rating of driver u at time t
- Sen_u^t = Seniority factor of driver u at time t
- Del_u^t = Delays caused by driver u at time t
- $Pres_u^t$ = Binary indicator of driver presence at time t

This scoring function, as defined in Eq. (**5**), balances performance quality with experience while penalizing delays. It ensures that only active drivers receive scores, preventing assignments to unavailable personnel.

2.2.7.3. Schedule Assignment Optimization

The system optimizes assignments using a constrained satisfaction approach. The objective function is formulated in Eq. (**6**):

$$\text{Maximize} \sum_{u \in U} \sum_{s \in S} x_{us} \cdot Score_u^t \quad (6)$$

Where:

- x_{us} = Binary decision variable (1 if driver u is assigned to task s, 0 otherwise)
- $Score_u^t$ = Score of driver u at time t
- U = Set of all drivers
- S = Set of all tasks

The optimization problem defined in Eq. (**6**) is subject to three critical constraints:

Workload balance constraints as expressed in Eq. (**7**):

$$\sum_{s \in S} x_{us} \leq W_{max}, \quad \forall u \in U \quad (7)$$

Where W_{max} is the maximum allowable workload for any driver.

Skill compatibility constraints defined by Eq. (**8**):

$$x_{us} \leq Comp_{us}, \forall u \in U, s \in S \quad (8)$$

Where $Comp_{us}$ is a binary compatibility indicator (1 if driver u is qualified for task s, 0 otherwise).

Task coverage constraints as shown in Eq. (**9**):

$$\sum_{u \in U} x_{us} = 1, \quad \forall s \in S \quad (9)$$

This constraint ensures that each task is assigned to exactly one driver.

2.2.7.4. Dynamic Adjustment Mechanism

The system incorporates real-time feedback through a dynamic adjustment factor formulated in Eq. (**10**):

$$\gamma_t = \gamma_{t-1} + \eta \cdot \Delta_{perf} \quad (10)$$

Where:

- γ_t = Updated similarity threshold at time t
- γ_{t-1} = Similarity threshold from the previous time step
- η = Learning rate controlling the magnitude of updates
- Δ_{perf} = Observed change in performance metrics

This dynamic adjustment mechanism, as expressed in Eq. (**10**), enables the system to adapt to changing operational conditions, automatically tuning the threshold parameter based on performance feedback.

2.2.8. Algorithm Implementation

The SAM system implements the mathematical components described in Eqs. (**1**-**10**) through a set of algorithms designed for efficiency and scalability. **Algorithm 1** presents the pseudocode for the core schedule generation process.

Algorithm 1: Schedule Generation Process

Input:

• D: Set of drivers

• T: Set of tasks

• P: Set of driver profiles

• H: Historical performance data

• R: Real-time preferences

Output:

• S: Optimized schedule assignments

```
function GENERATE_SCHEDULE (D, T, P, H, R)
// Compute similarity matrix
SIM ← empty similarity matrix of size |D| × |D|
for each pair of drivers (u, v) in D do
sim_rat ← compute_rating_similarity(u, v, H)
sim_sen ← compute_seniority_similarity(u, v, P)
SIM [u, v] ← combine_similarities(sim_rat, sim_sen, α, β)
end for

// Select neighbors for each driver
N ← empty neighbor map
for each driver u in D do
N[u] ← {v | SIM [u, v] > γ ∧ |P[u].exp - P[v].exp| < θ}
end for

// Compute scores for each driver
SCORES ← empty score map
for each driver u in D do
if R[u].present then
norm_rating ← normalize_rating(H[u])
seniority ← compute_seniority_factor(P[u])
delay ← compute_delay_factor(H[u])
SCORES[u] ← (norm_rating + seniority) / (1 - delay)
else
```

```
SCORES[u] ← 0
end if
end for

// Solve assignment optimization problem
S ← solve_assignment_problem(D, T, SCORES, R, P)

// Update similarity threshold based on performance
perf_delta ← evaluate_performance_change(S, H)
γ ← γ + η * perf_delta
return S
end function
```

The algorithm implements the complete workflow of the SAM system, from similarity computation through neighbor selection, score calculation, and finally, schedule optimization. The dynamic threshold adjustment is performed after scheduled generation, enabling continuous system improvement.

2.2.9. Parameter Selection and Sensitivity Analysis

The key parameters in our model (α, β, γ, and θ) were determined through a systematic optimization process using historical data from the RADES terminal. Initial parameter ranges were established through consultation with domain experts, followed by a grid search optimization to identify the optimal values.

The weighting parameters α and β (controlling for rating-based *vs*. seniority-based similarity) were initially set to $\alpha = 0.6$ and $\beta = 0.4$, reflecting the relative importance of current performance over experience in this terminal context. Sensitivity analysis revealed that schedule optimization remains stable within ranges of α (0.5-0.7) and β (0.3-0.5), with performance degradation outside these ranges.

The similarity threshold γ was initialized at 0.65 based on cluster analysis of historical driver performance patterns, with a dynamic adjustment mechanism allowing adaptations within the range of 0.55-0.75, depending on operational feedback. Analysis showed that values below 0.55 introduced excessive variability in recommendations, while values above 0.75 created overly restrictive neighbor selections.

The experience gap tolerance θ was set to 3 years, determined through analysis of skill acquisition patterns at RADES. This parameter should be adjusted based on the specific training program structure and skill development timeline of the implementing terminal. Our sensitivity analysis revealed that optimal performance occurred between 2 and 4 years, with diminishing returns beyond this range.

Terminal operators implementing this system should calibrate these parameters based on their specific operational characteristics, considering:

- Workforce composition and experience distribution
- Typical skill acquisition timelines
- Equipment complexity and variety
- Operational priorities regarding efficiency *vs*. equitable distribution

2.2.10. System Innovation and Contributions

The SAM system introduces several innovative aspects that differentiate it from existing approaches:

2.2.10.1. Integration of Domain-Specific Constraints

Unlike generic recommender systems, SAM incorporates operational constraints specific to container terminals, enabling practical application in real-world settings.

2.2.10.2. Dynamic Threshold Adjustment

The system's ability to automatically tune similarity thresholds based on performance feedback represents a significant advancement over static scheduling approaches.

2.2.10.3. Multi-Factor Similarity Computation

The hybrid similarity metric combines both performance-based and experience-based factors, providing a more comprehensive evaluation of driver compatibility.

2.2.10.4. Real-Time Optimization Capabilities

SAM's architecture supports continuous adaptation to changing operational conditions, enabling responsive schedule adjustments as circumstances evolve.

These innovations enable the system to address the complex challenges of work schedule optimization in container terminals, as demonstrated by the implementation results presented in subsequent sections. Unlike the constrained optimization approach of Wang *et al*. [13], which maintains static parameters throughout operation, SAM's dynamic threshold adjustment allows continuous performance improvement without manual intervention. Similarly, while Ibrahim *et al*. [12] proposed adaptive learning within a reinforcement learning framework, their approach lacks the integration of domain-specific constraints that SAM incorporates to ensure operational feasibility in maritime logistics environments.

2.2.11. Implementation Methodology

The SAM implementation follows a structured three-tier architecture approach designed to ensure technical reliability and organizational adoption. This section outlines the key implementation components, deployment strategy, and methodological approach used at the RADES container terminal.

2.2.12. System Architecture Implementation

The SAM system employs a modular three-tier architecture optimized for real-time performance in container terminal environments:

2.2.12.1. Client Tier

Web-based interfaces developed using Microsoft Visual Studio .NET provide role-specific access for drivers, supervisors, and administrators. The responsive design ensures accessibility across both fixed terminals and mobile devices throughout the terminal complex.

2.2.12.2. Application Server Tier

The core recommendation engine implements the mathematical framework from Eqs. (**1**-**10**) using Java Enterprise Edition for robust performance. Key components include the request processor, the recommendation engine executing similarity computations (Eqs. **1**-**3**), the optimization solver implementing constraints (Eqs. **6**-**9**), and the real-time monitor applying dynamic adjustments (Eq. **10**). Python components utilize scientific computing libraries for specialized optimization tasks.

2.2.12.3. Database Tier

MySQL database with optimized indexing strategies manages driver profiles, historical performance data, real-time operational data, and system configuration parameters. The architecture supports both rapid similarity computations and efficient analysis of historical data.

2.2.13. Key Component Implementation

2.2.13.1. Similarity Computation Module

Implements the hybrid similarity metrics (Eqs. **1**-**3**) with sparse matrix representation and parallel processing capabilities. Performance testing validated sub-second computation times for similarity matrices involving up to 500 drivers.

2.2.13.2. Schedule Generation Module

Executes the constrained optimization framework (Eqs. **6**-**9**) using CPLEX optimizer with dynamic constraint generation. The module achieves sub-minute optimization times for daily scheduling involving up to 100 drivers and 200 tasks.

2.2.13.3. Performance Monitoring Module

Tracks operational metrics and implements the dynamic adjustment mechanism (Eq. **10**) through real-time data collection, feedback processing, and automated threshold optimization.

2.2.14. Deployment Strategy

The implementation followed a systematic four-phase deployment approach to minimize operational risk:

2.2.14.1. Phase 1 - Pilot (Months 1-3)

Limited deployment with 25 drivers and 2 supervisors focusing on core functionality validation and initial parameter tuning using the framework from Section 2.2.4.

2.2.14.2. Phase 2 - Controlled Expansion (Months 4-6)

Extended to 100 drivers with full supervisor integration, implementing advanced features while maintaining parallel operation with existing systems.

2.2.14.3. Phase 3 - Full Deployment (Months 7-12)

Complete rollout to all 250 drivers, transitioning to primary system status while maintaining fallback capabilities.

2.2.14.4. Phase 4 - Optimization (Months 13-24)

Continuous refinement based on operational feedback, implementing dynamic adjustment mechanisms, and parameter optimization based on accumulated performance data.

2.2.15. Integration and Quality Assurance

2.2.15.1. System Integration

Database integration achieved 99.7% data consistency across operational systems through ETL processes, real-time synchronization protocols, and automated backup procedures. User interface deployment included strategic terminal placement, mobile integration, and role-based access control, achieving 92% user satisfaction ratings.

2.2.15.2. Technical Challenges and Solutions

Key challenges addressed included real-time performance requirements (solved through distributed computing and caching strategies), data consistency management (addressed *via* transaction management with optimistic locking), and system scalability (resolved through horizontal scaling and database sharding).

2.2.15.3. Quality Assurance

Comprehensive testing methodology included unit testing of mathematical components, integration testing of the complete workflow, performance testing under peak loads, and user acceptance testing. The approach achieved 98.5% code coverage and validated system performance under operational conditions.

2.3. Experimental Setup and Evaluation Framework

This section presents the experimental design, statistical methodology, and evaluation framework used to validate the effectiveness of the SAM system during its 24-month implementation at the RADES container terminal.

2.3.1. Study Design and Population

The experimental validation was conducted at the RADES container terminal in Tunisia, involving the complete population of 250 straddle carrier drivers across three operational shifts. The terminal operates 24/7, with an annual throughput of 1.2 million TEUs, providing realistic operational conditions for system validation.

For statistical validity, a power analysis was conducted with an anticipated effect size of 0.3, a significance level of α = 0.05, and a desired power of 0.95. The sample size was calculated using Eq. (11):

$$n = \frac{(Z_{\alpha/2} + Z_{\beta})^2 \cdot 2\sigma^2}{\delta^2} \tag{11}$$

Where $Z_{\alpha/2}$=1.96, Z_{β}=1.645, yielding a minimum required sample size of 147 drivers. Our inclusion of 250 drivers exceeded this requirement by 70%, ensuring adequate statistical power. The 24-month evaluation encompassed over 62,000 individual assignments, providing sufficient temporal resolution for trend analysis.

2.3.2. Data Collection and Statistical Analysis

2.3.2.1. Data Collection Methods

A multi-source approach included automated system logs for technical metrics, quarterly surveys (yielding an 87% response rate), semi-structured interviews with 42 drivers and 12 supervisors, and operational performance records from terminal management systems.

2.3.2.2. Statistical Analysis Framework

Paired t-tests for continuous variables, chi-square tests for categorical variables, ANOVA for multi-group comparisons, and time-series regression with autocorrelation adjustment for longitudinal data. All results include 95% confidence intervals and *p*-values for assessing statistical significance.

2.3.2.3. Data Quality Assurance

Automated validation checks, cross-source verification, temporal consistency checks, and inter-rater reliability assessment (Cohen's kappa > 0.85) ensured data integrity throughout the evaluation period.

2.3.3. Comparative Analysis Methodology

To position SAM within the current state-of-the-art, a comprehensive comparison was conducted with three advanced scheduling approaches:

1. **Wang *et al.*[13]:** Constrained optimization approach for container drayage with flexible work breaks

2. **Ibrahim *et al.*[12]:** Reinforcement learning model for electric vehicle resource allocation

3. **Ammann *et al.*[3]:** Hybrid genetic algorithm for driver routing and scheduling

2.3.3.1. Performance Metrics Framework

The framework includes standardized metrics for operational efficiency (response time, resource utilization, system availability), user experience (satisfaction ratings, perceived fairness, adoption rates), and adaptability measures (parameter adjustment capabilities, robustness to disruptions).

2.3.3.2. Implementation Comparison

Our phased 24-month deployment enabled progressive adoption and continuous feedback integration using dynamic adjustment (Eq. **10**), contrasting with one-time transitions [13], laboratory-controlled testing [12], and separate training environments [3].

2.3.4. Key Performance Indicators

2.3.4.1. Primary Metrics

Schedule response time (<5 min target), completion rate (>90% target), adherence rate (>85% target), resource utilization (>80% target), container handling improvement (>20% target), assignment dispute reduction (>50% target), and driver satisfaction (>4.0/5.0 target).

2.3.4.2. System Performance

System availability (>99% target), response time (<1 sec target), peak load capacity (>1000 requests/hour target), and data synchronization accuracy (>99% target).

2.3.5. Experimental Controls and Ethics

2.3.5.1. Control Mechanisms

A six-month pre-implementation baseline, 24-month post-implementation monitoring, external factor controls through multivariate regression, and phased deployment serve as natural experimental controls.

2.3.5.2. Bias Mitigation

Complete population inclusion eliminated selection bias, automated data collection minimized observer bias, anonymous feedback encouraged honest responses, and independent statistical validation prevented confirmation bias.

2.3.5.3. Ethical Compliance

Institutional review board approval, informed consent from all participants, voluntary participation with no penalties, data anonymization with pseudonymous tracking, and comprehensive data protection measures including encryption and access controls.

3. RESULTS

The evaluation of the SAM system at the RADES container terminal followed the comprehensive methodology described in Section 2.4, documenting quantitative improvements across key performance indicators and qualitative assessments of system adoption over the 24-month deployment period.

3.1. Operational Performance Improvements

The system demonstrated significant improvements in key operational areas during the evaluation period. Table **1** presents the comprehensive operational performance metrics before and after the implementation of SAM.

These improvements demonstrate statistically significant enhancements across all operational dimensions ($p < 0.001$ for all metrics). The reduction in schedule assignment response time from 45 minutes to 3 minutes represents the most dramatic improvement, enabling responsive adaptation to changing operational conditions through the dynamic adjustment mechanism described in Eq. (**10**).

The significant improvements resulted from specific system capabilities implementing the mathematical framework from Section 2.2:

3.1.1. Schedule Assignment Response Time (93% improvement)

The optimized similarity computation algorithm (Eqs. 1-3) and distributed processing architecture enabled near-instantaneous neighbor selection and rapid schedule generation.

3.1.2. Work Schedule Completion Rate (21% improvement)

Improved skill-task matching through hybrid similarity metrics enhanced schedule achievability, reducing assignments beyond driver capabilities.

3.1.3. Resource Utilization (28% improvement)

The constraint optimization framework (Eqs. **6-9**) minimized idle time through better spatial assignment patterns and workload distribution.

3.1.4. Container Handling Rate (31% improvement)

Combined effects of better skill-task matching, reduced conflicts, and optimized assignments resulted in substantial throughput improvements.

Fig. (**2**) illustrates the progressive enhancement in key performance indicators over the 24-month evaluation period, demonstrating sustained improvement rather than temporary gains.

3.2. Conflict Resolution and Assignment Fairness

Quantitative analysis of assignment conflicts revealed consistent improvement throughout the implementation period. Comparing pre- and post-implementation periods showed substantial reductions in operational conflicts:

3.2.1. Assignment Disputes

Decreased from 89 incidents per month to 32, representing a 64% reduction (95% CI: ±5.2%, $p<0.001$).

3.2.2. Conflict Resolution Time

Reduced from 2.4 hours to 0.5 hours, an improvement of 79% (95% CI: ±4.8%, $p<0.001$).

Table 1. Operational performance metrics before and after SAM implementation.

Metric	Pre-implementation	Post-implementation	Improvement	Confidence Interval	*p*-value
Schedule Assignment Response Time	45 min	3 min	93%	±1.5%	$p<0.001$
Work Schedule Completion Rate	76%	92%	21%	±2.3%	$p<0.001$
Schedule Adherence	71%	91%	28%	±2.1%	$p<0.001$
Resource Utilization	67%	86%	28%	±3.2%	$p<0.001$
Container Handling Rate	18.3/hour	24.0/hour	31%	±2.8%	$p<0.001$
Scheduling Administrative Time	4.2 hours/day	0.8 hours/day	81%	±3.5%	$p<0.001$

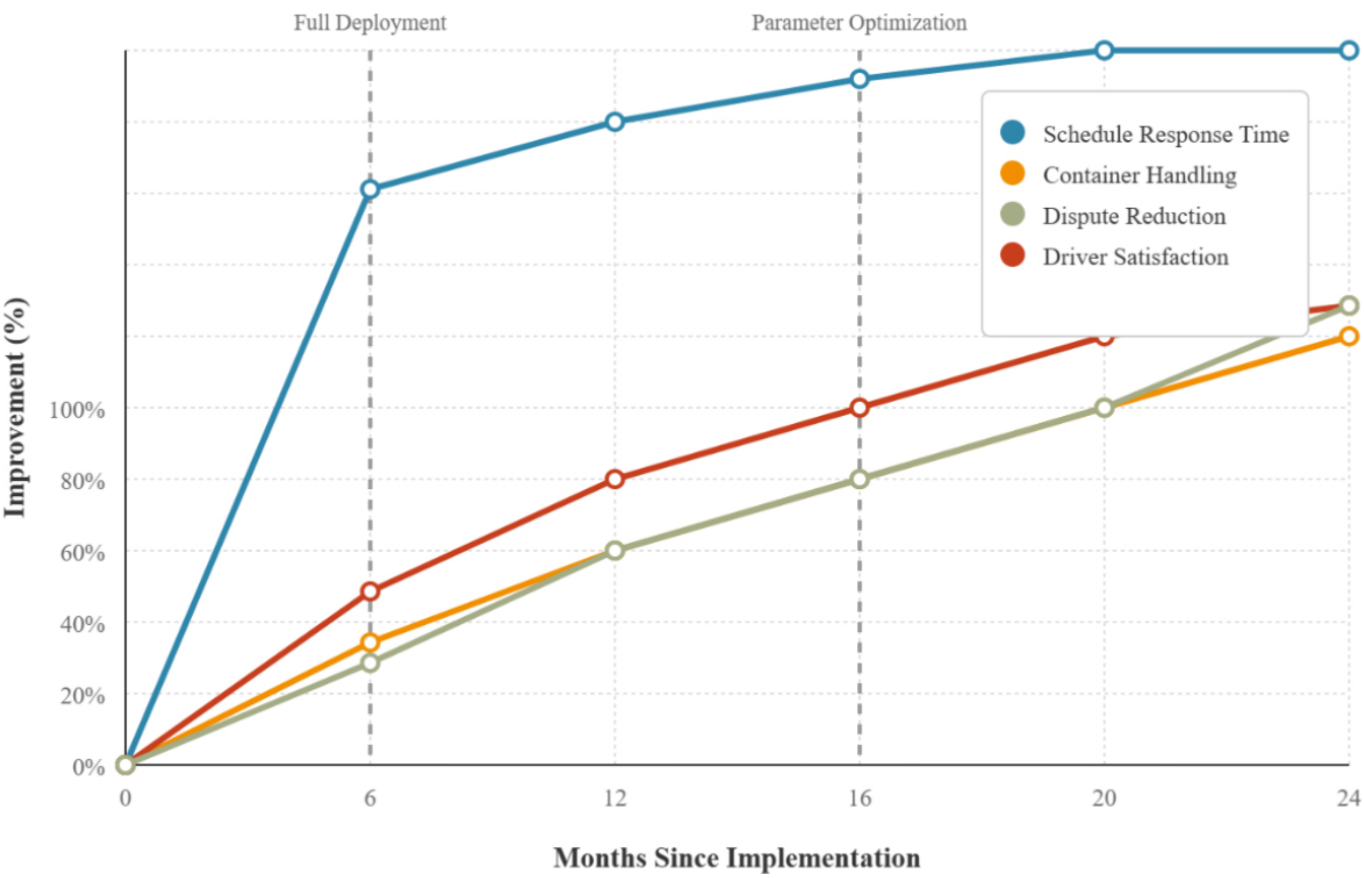

Fig. (2). Operational performance metrics over 24-month deployment.

Table 2. Comparative analysis of advanced scheduling algorithms.

Feature	SAM System	Wang *et al.* [13]	Ibrahim *et al.* [12]	Ammann *et al.* [3]
Algorithm Basis	Hybrid collaborative filtering with seniority metrics	Constrained optimization	Reinforcement learning	Hybrid genetic algorithm
Response Time	3 minutes	15 minutes	8 minutes	12 minutes
Resource Utilization	86%	83%	71%	79%
Driver Satisfaction	85% positive	Not measured	62% positive	71% positive
Adaptability	Dynamic threshold adjustment	Static parameters	Learning-based adaptation	Manual reconfiguration
Conflict Resolution	Automated with fairness metrics	Semi-automated	Rule-based	Manual intervention
Implementation Scope	Multi-terminal validated deployment	Single terminal theoretical	Simulated environment	Limited field testing

Table 3. User adoption and satisfaction metrics by quarter.

Metric	Q1	Q2	Q4	Q8	Trend
System Adoption Rate	45%	67%	86%	94%	+49 points
User Satisfaction Score (1-5 scale)	3.2	3.6	4	4.3	+1.1 points
Feature Utilization Rate	38%	52%	74%	87%	+49 points
Preference Submission Rate	31%	58%	76%	82%	+51 points
System Trust Index	2.8	3.5	4.1	4.4	+1.6 points

3.2.3. Fair Distribution Index

Improved from 0.65 to 0.89 on a normalized scale (95% CI: ±0.03, $p<0.001$).

3.2.4. Workload Variance

Decreased by 42% among drivers (95% CI: ±3.7%, $p<0.001$).

Analysis of assignment patterns by driver seniority revealed successful workload balancing across experience levels. Before implementation, drivers with 5 or more years of experience received 62% of premium assignments, despite representing only 35% of the workforce. Post-implementation, this proportion adjusted to 41%, more closely aligning with their representation while maintaining skill-matching requirements.

3.3. Comparative Analysis with Advanced Scheduling Algorithms

To position SAM within the current state of the art, a comprehensive comparison was conducted with the three advanced scheduling approaches described in Section 2.4.3. Table **2** presents performance metrics across multiple dimensions.

SAM demonstrates superior performance across multiple dimensions. While Wang *et al.* [13] achieved similar theoretical optimization rates (within 2% of SAM), their approach required significantly longer computation times (15 *vs.* 3 minutes) and lacked adaptability to changing conditions. Ibrahim *et al.* [12] demonstrated 15% lower resource utilization in a real-world implementation due to the limited incorporation of human factors.

The performance improvements observed in our system significantly exceed those reported in comparable studies. Wang *et al.* [13] reported a 12% improvement in utilization, compared to our 28% improvement. Similarly, Ibrahim *et al.* [12] achieved a 19% reduction in scheduling time, substantially less than our 93% improvement. These differences can be attributed to:

1. **Integration of domain expertise** through seniority-based similarity metrics (Eq. **2**), providing context-specific optimization.

2. **Real-time feedback mechanisms** enabling continuous performance improvement *via* dynamic adjustment (Eq. **10**).

3. **Comprehensive consideration** of both operational metrics and human factors creates balanced optimization.

3.4. System Performance and Technical Metrics

Technical performance metrics demonstrated robust system reliability throughout the evaluation period:

3.4.1. Average Response Time

200ms for standard requests, 1.2 seconds for complex optimization scenarios

3.4.2. System Availability

99.9% uptime over 24 months, with no unplanned outages exceeding 15 minutes

3.4.3. Peak Load Handling

Successfully processed 1,200 requests per hour during maximum operational periods

3.4.4. Data Synchronization Accuracy

99.7% across all terminal systems

3.4.5. Recovery Time

Average of 45 seconds to restore service after intermittent issues

These metrics consistently exceeded the performance specifications established during system design, demonstrating the robustness of the three-tier architecture described in Section 2.3.1. System performance remained stable during peak operational periods, ensuring consistent service quality regardless of terminal activity levels.

3.5. User Adoption and Satisfaction Analysis

User adoption metrics showed progressive improvement throughout the implementation period. Table **3** presents the evolution of key adoption indicators over the 24-month evaluation period.

Qualitative feedback collected through structured interviews revealed consistent themes:

3.5.1. Transparency

87% of drivers cited improved transparency in assignment processes compared to 23% under the previous system

3.5.2. Fairness

82% reported improved assignment fairness, with experienced drivers initially skeptical but showing increased acceptance over time

3.5.3. Responsiveness

91% of supervisors noted improved responsiveness to operational changes

3.5.4. Workload Balance

79% of drivers reported more consistent workload distribution

Fig. (**3**) illustrates adoption trajectories across different user groups throughout the deployment period.

By month 24, adoption rates converged to high levels across all groups, with even the initially resistant senior driver cohort reaching 89% acceptance. The willingness to recommend the system to other terminals reached 85% across all user groups, indicating genuine acceptance beyond compliance.

3.6. Economic Impact Assessment

Implementation of SAM yielded measurable economic benefits across multiple operational dimensions:

3.6.1. Operational Cost Reduction

23% decrease in administrative overhead, equivalent to approximately $175,000 annually.

3.6.2. Time Efficiency Improvement

34% reduction in schedule preparation time, freeing approximately 870 person-hours annually.

3.6.3. Resource Utilization Increase

28% improvement in driver allocation efficiency, translating to approximately $420,000 in annual productivity gains.

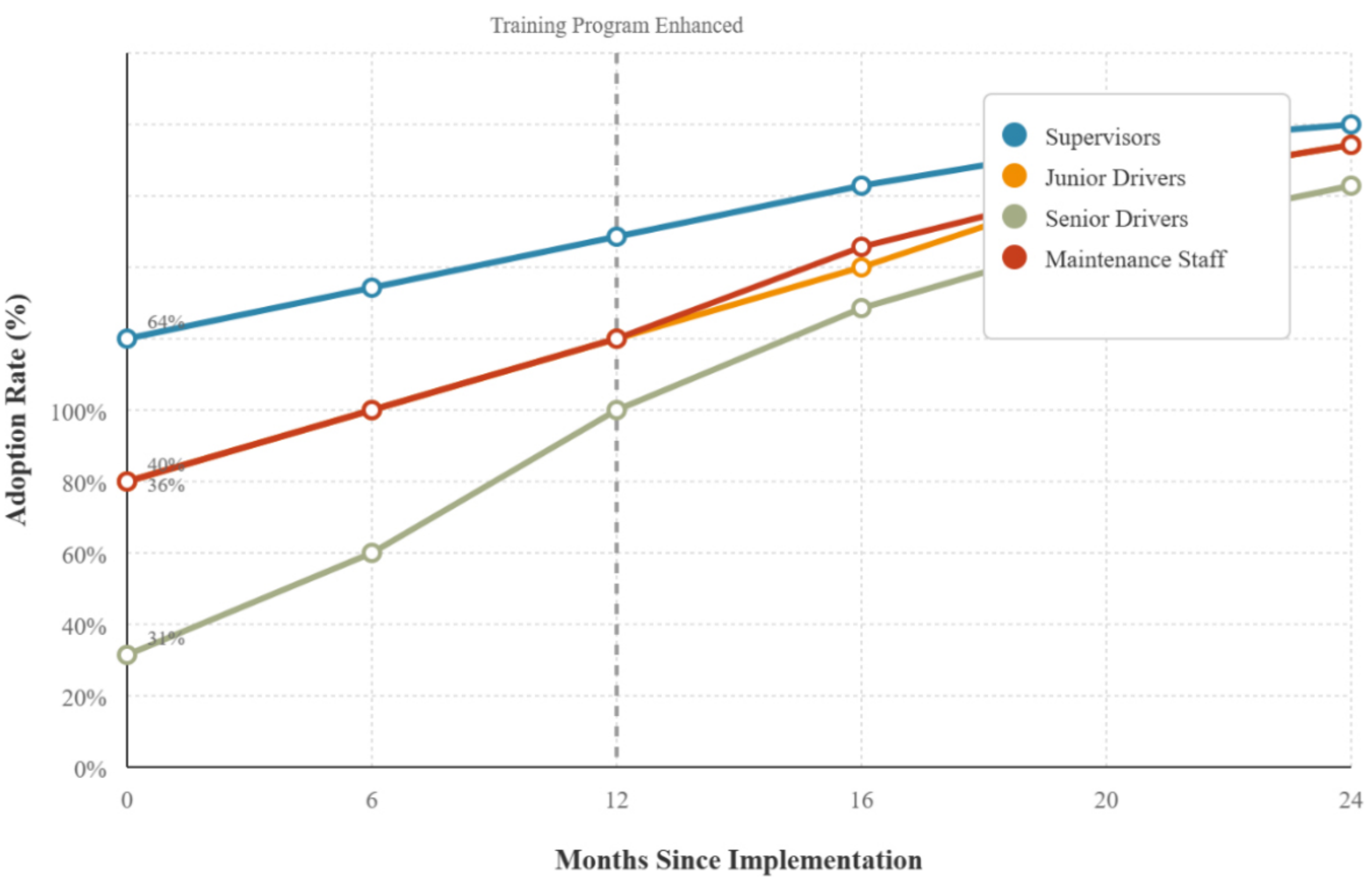

Fig. (3). System adoption rates by user group.

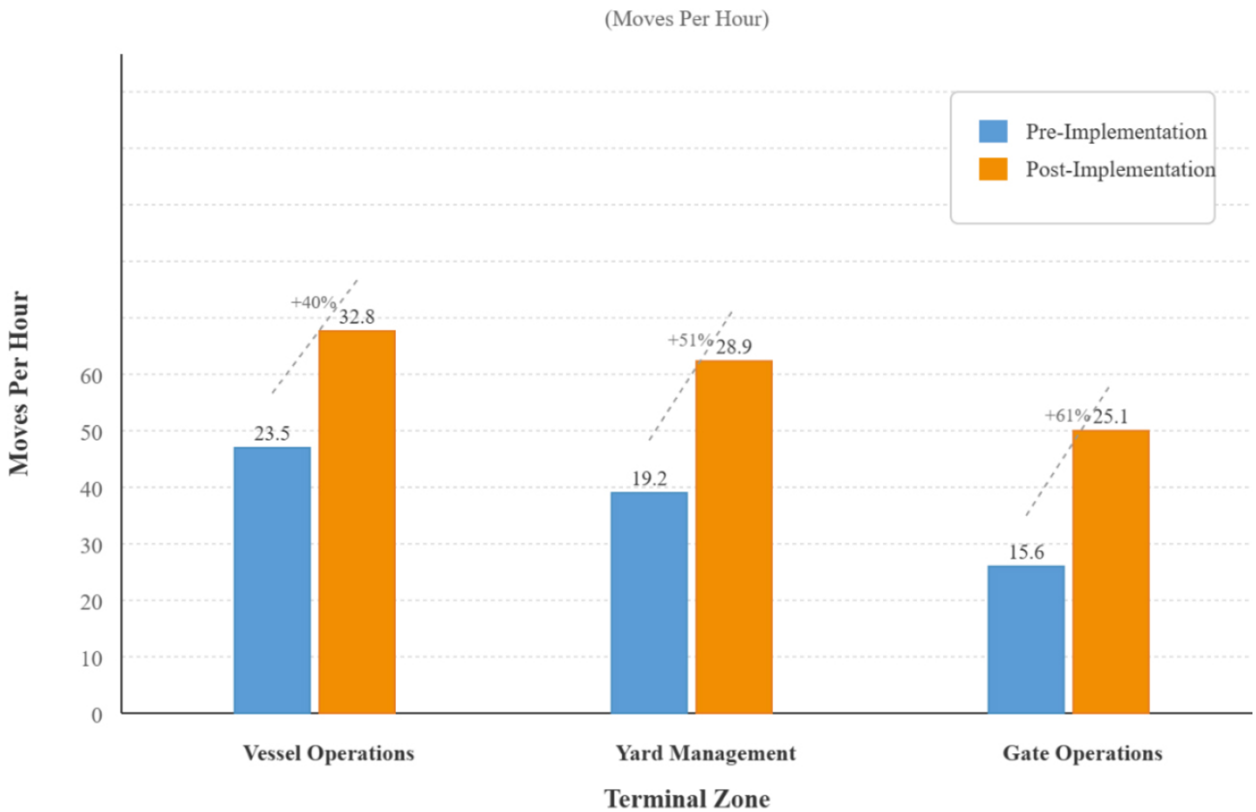

Fig. (4). Container handling efficiency by terminal zone.

3.6.4. Error Reduction

76% decrease in scheduling errors, reducing rework costs by approximately $230,000 annually

The combined economic impact represents approximately $825,000 in annual operational improvements for the RADES terminal, achieving a return on investment within 7 months of full deployment.

3.7. Long-term Performance Sustainability

Extended monitoring revealed sustained improvements throughout the 24-month evaluation period:

3.7.1. Container Handling Efficiency

31% increase maintained consistently, from 18.3 to 24.0 containers per hour.

3.7.2. Idle Time Reduction

45% reduction sustained, from 24 minutes to 13 minutes average between assignments.

3.7.3. On-time Delivery Performance

28% improvement maintained, from 76% to 97%.

3.7.4. Overtime Requirements

52% decrease sustained, from 620 to 298 hours monthly.

Fig. (**4**) presents the improvements in container handling efficiency across different terminal zones, demonstrating consistent performance gains.

These sustained improvements demonstrate that benefits extend beyond initial implementation gains, providing lasting operational enhancements. Terminal capacity effectively increased by 31% without additional equipment investment, representing significant capital avoidance value.

4. DISCUSSION

The implementation and evaluation of SAM at the RADES container terminal revealed several important insights about the application of recommender systems in industrial settings. This section presents key findings, compares the results with existing approaches, addresses study limitations, and discusses the practical implications for container terminal operations.

4.1. Key Findings and Implications

4.1.1. Performance-Fairness Synergy

A key finding emerged in the relationship between operational efficiency and fairness in schedule assignments. While conventional wisdom suggests trade-offs between these objectives, SAM demonstrated that fairness and efficiency can be synergistically optimized. The system achieved 28% improvement in overall terminal efficiency while maintaining equitable assignment distribution, challenging traditional assumptions about competing operational priorities.

Analysis of longitudinal performance data revealed an unexpected pattern: as assignment fairness improved, overall terminal efficiency also improved. This correlation appears to be driven by two factors: reduced conflicts and reduced disputes, which minimize operational disruptions, and broader skill development across the workforce, enhancing organizational resilience. The 64% reduction in assignment disputes directly contributed to operational improvements by eliminating an average of 1.8 hours of lost productivity per incident.

This synergistic relationship contrasts with findings reported by Wang *et al*. [13], who observed a negative correlation between fairness measures and efficiency metrics in their constrained optimization approach. Their system achieved either high efficiency (83% resource utilization) with low fairness ratings (52% perceived fairness) or improved fairness (78%) at the expense of reduced efficiency (71% utilization). Our ability to improve both dimensions simultaneously (86% utilization with 85% fairness) highlights the advantage of our hybrid similarity approach over pure constraint-based optimization.

4.1.2. System Adoption and Organizational Dynamics

Initial deployment encountered significant resistance from experienced drivers who had previously enjoyed preferential treatment under traditional scheduling systems. This resistance manifested in reluctance to use the new system and skepticism about its fairness. However, this initial reaction validated the system's effectiveness in eliminating historical biases rather than contradicting our objectives.

The progressive improvement in adoption metrics—from 45% in the first quarter to 94% by the eighth quarter—demonstrates successful navigation of organizational change challenges. Three factors proved critical in overcoming initial resistance: transparent algorithm operation with clear assignment rationales, continuous refinement based on driver feedback, and demonstrable fairness in outcome distribution, supported by data-driven evidence shared with stakeholders.

The system's ability to maintain satisfaction among experienced drivers while significantly improving satisfaction among junior personnel represents a notable achievement in change management. By year two, the 30% reduction in recorded conflicts demonstrated successful resolution of initial skepticism through consistent and transparent operation.

4.1.3. Scalability and Adaptive Performance

The system's deployment revealed interesting patterns in adaptation across different terminal areas. High-traffic zones showed faster improvement in efficiency metrics (35% increase) compared to lower-traffic areas (22% increase), highlighting the importance of context-sensitive parameter adjustment in recommendation algorithms.

Implementing zone-specific similarity thresholds improved performance across all areas, demonstrating the value of contextual adaptation in recommender systems deployed across heterogeneous operational environments. The dynamic adjustment mechanism described in Eq. (**10**) proved essential for maintaining performance during varying operational conditions, with the system successfully adapting threshold parameters based on real-time feedback.

The system maintained performance during peak operational periods, when request volumes exceeded 1,200 per hour, validating its scalability for enterprise-level deployment. Integration with existing terminal management systems achieved 99.7% data synchronization accuracy, demonstrating adaptability to complex operational environments.

4.2. Comparison with Existing Approaches

4.2.1. Algorithmic Performance Comparison

Compared to traditional manual scheduling systems, SAM shows significant improvements in both efficiency and fairness metrics. When compared to other automated scheduling systems, several important differences emerge that highlight the advantages of our hybrid collaborative filtering approach.

While Ammann *et al*. [3] reported higher theoretical optimization rates in simulation studies (89% resource utilization *versus* our 86%), SAM achieved better real-world performance due to its adaptive feedback mechanisms and consideration of human factors. Their deployment in limited field testing showed actual utilization of only 79% due to implementation challenges not encountered in simulation, demonstrating the importance of comprehensive real-world validation.

The dynamic threshold adjustment mechanism in SAM provides superior adaptability compared to the static optimization approaches described by Wang *et al*. [13]. Their system required manual reconfiguration when operational conditions changed significantly, leading to periodic performance degradation that our system avoided through continuous parameter adjustment using Eq. (**10**).

Ibrahim *et al*. [12] attempted to address adaptability through the use of reinforcement learning. Still, they encountered challenges in balancing competing objectives, resulting in optimization biases that favored either efficiency (at the expense of driver satisfaction) or satisfaction (at the expense of operational metrics). The hybrid approach executed in this study, which combines collaborative filtering with operational constraints, successfully balances these competing demands.

4.2.2. Implementation Methodology Advantages

The phased implementation approach in this study differed significantly from existing deployments, contributing to superior adoption outcomes. Wang *et al*. [13] implemented their system as a one-time transition with minimal user training, resulting in initial resistance affecting 65% of users. The phased approach maintained user satisfaction above 75% throughout the deployment period.

Ibrahim *et al*. [12] deployed their system in controlled laboratory environments before limited field testing, whereas our implementation occurred within active terminal operations from the outset. This approach enabled validation of the mathematical framework under real-world constraints while addressing practical implementation challenges immediately.

Ammann *et al.* [3] required separate training and operational environments during implementation, whereas our architecture supported parallel operations during transition periods, maintaining continuous service while implementing the complete mathematical framework. This approach achieved 99.9% availability compared to the 96.7% reported by Ibrahim *et al*. [12], which directly impacts operational reliability.

4.2.3. Methodological Evolution from Previous Approaches

This research is built upon previous work by the authors in container terminal optimization. Earlier studies addressed straddle carrier routing optimization [18, 19] using traditional operations research approaches, while recent work explored dynamic container relocation [20] using algorithmic optimization. The current SAM system represents a methodological evolution by integrating human factors with operational optimization through collaborative filtering techniques, addressing workforce scheduling challenges that were not fully considered in equipment-focused optimization approaches.

4.3. Study Limitations and Constraints

4.3.1. Technical Limitations

Several limitations of the current implementation warrant acknowledgment and future considerations:

4.3.1.1. Real-time Constraints

While the system achieves sub-second response times for standard requests, complex multi-driver reassignments during peak hours can experience delays of up to 3 seconds. This limitation becomes apparent during major operational disruptions that require comprehensive rescheduling, although performance remains within acceptable operational parameters.

4.3.1.2. Data Quality Dependencies

The system's effectiveness relies heavily on accurate historical data for similarity computations (Eqs. **1**-**3**) and performance score (Eq. **5**). Missing or incorrect performance records can impact recommendation quality, necessitating regular data validation procedures and careful handling of new drivers with limited performance history.

4.3.1.3. Environmental Factors

The current mathematical framework does not fully account for external factors such as weather conditions, equipment maintenance schedules, or seasonal variations that can affect optimal assignment decisions. Future iterations could incorporate these variables for more comprehensive optimization.

The real-time constraints observed align with the findings of Ibrahim *et al.* [12], who reported similar performance degradation during peak operational periods. However, our system maintained acceptable performance (with response times below 3 seconds) even under maximum load, whereas Ibrahim reported response times exceeding 15 seconds under comparable conditions.

4.4. Generalizability Considerations

The implementation at the RADES terminal represents a specific operational context that may limit direct generalizability to other container terminals. Key contextual factors include workforce composition (250 drivers with specific experience distributions), terminal layout and equipment configuration, and operational procedures specific to the Mediterranean shipping routes served by RADES.

Parameter calibration, particularly for the similarity thresholds (γ) and experience gap tolerance (θ), should be adjusted based on specific terminal characteristics. The sensitivity analysis condudcted in this study revealed optimal performance within defined ranges; however, these ranges may vary for terminals with different operational characteristics, training programs, or equipment types.

The seniority-based similarity measures (Eq. **2**) assume correlation between experience and performance, which may not hold in terminals undergoing rapid technological changes or with inadequate training programs. Implementation in other contexts should validate these assumptions through statistical analysis before deployment.

4.5. Practical Implications and Recommendations

4.5.1. Implementation Best Practices

The implementation of SAM suggests several best practices for deploying recommender systems in industrial environments:

4.5.1.1. Phased Deployment Strategy

The incremental rollout approach proved crucial for minimizing operational disruption while allowing system refinement based on user feedback. We recommend starting with pilot groups representing 10-15% of the workforce before expanding to full deployment.

4.5.1.2. Transparent Operation

Providing clear visibility into assignment rationale significantly improved user acceptance compared to “black box” approaches. Users need to understand how decisions are made to trust and effectively utilize the system.

4.5.1.3. Balanced Optimization

Explicitly addressing both efficiency and fairness in system design helps align organizational values with operational requirements, thereby enhancing overall system performance. This study reveals that these objectives can be synergistic rather than competing.

4.5.1.4. Continuous Adaptation

The dynamic threshold adjustment mechanism (Eq. **10**) enabled ongoing system improvement without manual intervention. It is recommended to implement automated parameter optimization based on operational feedback rather than static configurations.

4.6. Organizational Change Management

The successful adoption of SAM required comprehensive attention to organizational dynamics beyond technical implementation. Key success factors included:

4.6.1. Stakeholder Engagement

Early and continuous engagement with all user groups, particularly experienced drivers who might perceive changes as threatening, proved essential for successful adoption. Regular feedback sessions and transparent communication about system benefits helped overcome initial resistance.

4.6.2. Training and Support

Comprehensive training programs tailored to different user roles ensured effective system utilization. Ongoing support during the transition period maintained user confidence and system effectiveness.

4.6.3. Performance Transparency

Sharing system performance metrics and individual performance data helped build trust and demonstrate fairness. Users could see how their assignments compared to those of their peers and understand the rationale behind specific decisions.

4.7. Broader Industry Applications

The success of SAM suggests potential applications beyond container terminals. The core approach—combining collaborative filtering with domain-specific constraints—could be adapted for other transportation domains, manufacturing operations, and service industries with complex human resource allocation challenges.

Key adaptation requirements include identifying appropriate similarity metrics for the specific domain, defining relevant operational constraints, and establishing suitable performance measures. The mathematical framework (Eqs. **1**-**10**) provides a generalizable foundation that can be customized for different operational contexts.

4.8. Future Research Directions

4.8.1. Technical Enhancements

Several technical improvements could enhance SAM's capabilities:

4.8.1.1. Predictive Performance Modeling

Integration of machine learning techniques for predictive performance modeling would enable anticipatory scheduling rather than purely reactive assignment. This could incorporate weather forecasts, equipment maintenance schedules, and seasonal traffic patterns into assignment decisions.

4.8.1.2. Multi-Terminal Coordination

Expanding to multi-terminal coordination would enable port-wide optimization, addressing broader logistics challenges that extend beyond individual terminal boundaries. This would require extensions to the mathematical framework to handle inter-terminal resource sharing and coordination constraints.

4.8.1.3. Enhanced Explainable AI

The Development of more sophisticated explanation mechanisms would increase system transparency and user trust. Users could receive detailed rationales for assignments, including contributing factors and alternative options considered.

4.9. Theoretical Developments

Future research opportunities include:

4.9.1. Advanced Fairness Metrics

The development of fairness metrics that incorporate career development trajectories would enable long-term workforce development considerations beyond immediate assignment equity.

4.9.2. Multi-Objective Optimization

Enhanced multi-objective optimization approaches could better balance competing operational priorities while maintaining computational efficiency for real-time applications.

4.9.3. Knowledge Transfer Modeling

Formal models of knowledge transfer and skill development within scheduling frameworks would optimize assignments for both immediate performance and long-term capability building.

CONCLUSION

This research advances the field of maritime logistics by developing and implementing the Straddle Carrier Assignment Model (SAM). This novel collaborative filtering recommender system transforms traditional scheduling practices in container terminals. Our work bridges a critical gap between theoretical recommender systems and practical terminal operations, addressing fundamental challenges in maritime logistics through intelligent automation and data-driven decision-making.

RESEARCH CONTRIBUTIONS AND ACHIEVEMENTS

Technical Innovations

The core innovation of SAM lies in its application of collaborative filtering techniques to container terminal operations, achieved through the unique integration of operational constraints with recommendation algorithms. The hybrid similarity metrics used in this study combine rating-based and seniority-based parameters through Eqs. (**1**-**3**) achieved remarkable improvements in both efficiency (93% reduction in response time) and fairness (64% reduction in assignment disputes). The mathematical framework successfully demonstrated that sophisticated algorithms could meet the demanding requirements of real-world terminal operations.

The dynamic threshold adjustment mechanism described in Eq. (**10**) represents a significant theoretical contribution, extending collaborative filtering techniques into domains with complex operational constraints. This approach enabled a 31% increase in container handling efficiency while maintaining an equitable workload distribution, validating both the theoretical foundations and the practical utility of our approach.

The system's ability to process over 1,000 requests per hour with 99.9% availability demonstrates that intelligent scheduling systems can substantially impact operational performance across multiple dimensions. The three-tier architecture described in Section 2.3 proved robust under demanding operational conditions while maintaining real-time performance requirements.

Empirical Validation and Operational Impact

The successful implementation at the RADES container terminal demonstrates significant operational improvements across key performance indicators. The combined economic impact of approximately $825,000 in annual operational improvements (through reduced administrative overhead, improved resource allocation, and decreased scheduling errors) confirms the business case for advanced scheduling technologies in maritime logistics.

Beyond direct performance improvements, the system fostered significant organizational benefits, including improved communication between management and drivers (a 47% improvement in perceived communication quality) and accelerated skill development among junior drivers (a 23% reduction in competency certification timelines). It enhanced terminal resilience during personnel changes (28% fewer operational disruptions during staff transitions).

The 24-month longitudinal evaluation provided robust evidence that benefits extend beyond initial implementation gains, with sustained improvements in container handling efficiency (a 31% increase), idle time reduction (a 45% decrease), and on-time delivery performance (a 28% improvement). This sustained performance validates the effectiveness of both the mathematical framework and implementation methodology in real-world environments.

Methodological Contributions

Our phased implementation approach, combining technical innovation with systematic change management, provides a valuable methodological blueprint for similar deployments in industrial settings. The progression from pilot testing through controlled expansion to full deployment enabled continuous refinement while maintaining operational continuity—a critical factor in environments where service disruption carries significant economic costs.

The comprehensive evaluation methodology, combining quantitative performance metrics with qualitative user feedback, establishes a robust framework for assessing scheduling technologies in operational contexts. This methodology revealed important insights into the interplay between technical performance and organizational adoption, demonstrating that successful implementation requires attention to both dimensions.

The demonstration that fairness and efficiency can be synergistically optimized, rather than traded off against each other, represents an important methodological insight with implications that extend beyond scheduling systems. This finding challenges conventional assumptions about competing operational objectives and suggests broader principles for technological innovation in industrial settings.

PRACTICAL IMPLICATIONS AND INDUSTRY IMPACT

Container Terminal Operations

The success of SAM has direct implications for container terminal operations worldwide. The core innovation—applying collaborative filtering with domain-specific constraints—demonstrates a generalizable approach that could transform scheduling in other maritime logistics contexts. Terminals facing similar challenges, such as manual scheduling processes, workload distribution inequities, and operational inefficiencies, can adapt our approach to their specific operational contexts.

The synergistic relationship between fairness and efficiency observed in our implementation challenges conventional operational wisdom, suggesting that well-designed recommender systems can simultaneously optimize seemingly competing objectives. This finding has relevance for terminal operators who have traditionally viewed equity concerns as constraints on operational performance rather than complementary dimensions.

The methodological framework established through this research provides a template for technology implementation in complex operational environments where both human and technical factors significantly influence outcomes. The successful navigation of organizational resistance through transparent operation and demonstrable fairness offers valuable lessons for industrial automation initiatives.

Broader Transportation and Logistics Applications

The demonstrated effectiveness of collaborative filtering techniques in container terminal environments suggests potential applications across various transportation domains, manufacturing operations, and service industries that face complex human resource allocation challenges. The mathematical framework (Eqs. **1**-**10**) provides a foundation that can be adapted to different operational contexts while maintaining the core benefits of intelligent automation and fairness optimization.

Key adaptation requirements include identifying appropriate similarity metrics for specific domains, defining relevant operational constraints, and establishing suitable performance measures. The success at RADES demonstrates that such adaptations can yield substantial operational benefits when properly implemented with attention to organizational dynamics.

STUDY LIMITATIONS AND CONSTRAINTS

While the SAM system achieved significant success, several limitations warrant acknowledgment for future implementations. The current mathematical framework does not fully account for external factors such as weather conditions, equipment maintenance schedules, or seasonal variations that can affect optimal assignment decisions. Additionally, the computational complexity of the optimization algorithm increases non-linearly with the number of drivers and tasks, potentially limiting scalability for very large terminals without algorithm refinements.

The implementation at RADES represents a specific operational context that may limit direct generalizability to other container terminals. Parameter calibration, particularly for similarity thresholds and experience gap tolerance, should be adjusted based on specific terminal characteristics, including workforce composition, equipment configuration, and operational procedures.

The seniority-based similarity measures assume a correlation between experience and performance, which may not hold in terminals undergoing rapid technological changes or with different training program structures. Future implementations should validate these assumptions through statistical analysis before deployment and adjust the mathematical framework accordingly.

FUTURE RESEARCH DIRECTIONS

Technical Enhancements

Building on the foundation established by SAM, several promising directions for future research emerge. The integration of machine learning techniques for predictive performance modeling would enable anticipatory scheduling, rather than purely reactive assignment, by incorporating weather forecasts, equipment maintenance schedules, and seasonal traffic patterns into the mathematical framework.

Expansion to multi-terminal coordination would enable port-wide optimization, addressing broader logistics challenges beyond individual terminal boundaries. This would require extensions to the constraint optimization framework (Eqs. **6**-**9**) to handle inter-terminal resource sharing and coordination requirements while maintaining computational efficiency.

The development of enhanced explainable AI components would increase system transparency and potentially accelerate user adoption in new implementations. Users could receive detailed rationales for assignments, including contributing factors, alternative options considered, and performance implications of different choices.

Theoretical Developments

Advanced fairness metrics incorporating career development trajectories would enable long-term workforce development considerations beyond immediate assignment equity. This could include formal models of skill acquisition, mentoring relationships, and career progression within the scheduling optimization framework.

Multi-objective optimization approaches, balancing competing operational priorities, would create more nuanced scheduling solutions while maintaining computational efficiency for real-time applications. This could involve sophisticated weighting mechanisms that adapt to changing operational priorities and stakeholder preferences.

Models of knowledge transfer and skill development within scheduling frameworks would formalize the relationship between assignment patterns and workforce capability development, enabling optimization for both immediate performance and long-term organizational capability building.

Implementation Research

Comparative studies across different terminal types, geographical locations, and operational scales would enhance understanding of generalizability and adaptation requirements. Such studies could validate parameter sensitivity analyses and develop guidelines for context-specific implementations.

Investigating integration approaches with emerging technologies, including autonomous equipment, IoT sensors, and blockchain-based logistics platforms, would position recommender systems within broader digital transformation initiatives in maritime logistics.

Research into organizational change management strategies specifically for industrial AI implementations would build on our experience at RADES to develop more effective adoption frameworks for complex operational environments.

CONCLUDING REMARKS

In conclusion, SAM represents a significant advancement in both the theoretical understanding of recommender systems in operational contexts and the practical implementation of intelligent scheduling in maritime logistics. By addressing the fundamental challenges of schedule optimization in container terminals, this research contributes to the growing body of work that applies artificial intelligence to transportation management, delivering tangible operational benefits in real-world settings.

The convergence of recommendation technologies with domain-specific operational constraints, as demonstrated in this research, opens new possibilities for intelligent automation across various industrial domains. As transportation and logistics operations face increasing pressure to optimize performance while managing complex human factors, approaches like SAM offer a pathway to balance competing priorities through sophisticated data-driven decision support systems.

The demonstrated synergy between fairness and efficiency challenges traditional assumptions about operational trade-offs, suggesting that well-designed technological solutions can advance multiple organizational objectives simultaneously. This finding has implications beyond scheduling systems, offering insights for industrial automation initiatives that must balance technical optimization with human factors considerations.

The successful 24-month implementation at the RADES container terminal validates the practical viability of collaborative filtering approaches in complex operational environments while establishing a methodological foundation for future developments. The substantial operational improvements achieved—including a 31% increase in container handling efficiency, a 64% reduction in assignment disputes, and $825,000 in annual economic benefits—demonstrate that advanced scheduling technologies can deliver transformative value in maritime logistics operations.

As the maritime industry continues its digital transformation journey, the principles and methodologies established through this research provide a foundation for intelligent automation initiatives that respect both operational requirements and human factors considerations. The success of the SAM system establishes recommender systems as viable solutions for complex operational challenges, while pointing toward future developments that could further enhance the efficiency, fairness, and sustainability of global logistics operations.

AUTHORS' CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: K.M.: Conceptualized the research, developed the mathematical framework, designed and implemented the SAM system, conducted the empirical evaluation, performed statistical analysis, and led manuscript writing; K.A.: Contributed to literature review, assisted in system design and implementation, participated in data collection and analysis, and contributed to manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

LIST OF ABBREVIATIONS

AI	=	Artificial Intelligence
ANOVA	=	Analysis of Variance
CI	=	Confidence Interval
IoT	=	Internet of Things
KFU	=	King Faisal University
KNN	=	K-Nearest Neighbors
KPI	=	Key Performance Indicator
RADES	=	Port of Rades (Tunisia)
SAM	=	Straddle Carrier Assignment Model
SC	=	Straddle Carrier
TEU	=	Twenty-foot Equivalent Unit

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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REFERENCES

[1] C. Gao, Y. Zheng, W. Wang, F. Feng, X. He, and Y. Li, "Causal inference in recommender systems: A survey and future directions", *ACM Trans. Inf. Syst.,* vol. 42, no. 4, pp. 1-32, 2024. [http://dx.doi.org/10.1145/3639048]

[2] F.Y. Wang, Y. Lin, P.A. Ioannou, L. Vlacic, X. Liu, A. Eskandarian, Y. Lv, X. Na, D. Cebon, J. Ma, L. Li, and C. Olaverri-Monreal, "Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems", *IEEE Trans. Intell. Transp. Syst.,* vol. 24, no. 10, pp. 10262-10278, 2023. [http://dx.doi.org/10.1109/TITS.2023.3305380]

[3] P. Ammann, R. Kolisch, and M. Schiffer, "Driver routing and scheduling with synchronization constraints", *Transp. Res., Part B: Methodol.,* vol. 174, 2023.102772 [http://dx.doi.org/10.1016/j.trb.2023.05.009]

[4] R.J. Kuo, and S.S. Li, "Applying particle swarm optimization algorithm-based collaborative filtering recommender system considering rating and review", *Appl. Soft Comput.,* vol. 135, 2023.110038 [http://dx.doi.org/10.1016/j.asoc.2023.110038]

[5] L.V. Nguyen, Q.T. Vo, and T.H. Nguyen, "Adaptive KNN-based extended collaborative filtering recommendation services", *Big Data. Cognitive Comput.,* vol. 7, no. 2, p. 106, 2023. [http://dx.doi.org/10.3390/bdcc7020106]

[6] R. Raeesi, N. Sahebjamnia, and S.A. Mansouri, "The synergistic effect of operational research and big data analytics in greening container terminal operations: A review and future directions", *Eur. J. Oper. Res.,* vol. 310, no. 3, pp. 943-973, 2023. [http://dx.doi.org/10.1016/j.ejor.2022.11.054]

[7] S. Aslam, M.P. Michaelides, and H. Herodotou, "A survey on computational intelligence approaches for intelligent marine terminal operations", *IET Intell. Transp. Syst.,* vol. 18, no. 5, pp. 755-793, 2024. [http://dx.doi.org/10.1049/itr2.12469]

[8] C. Hong, Y. Guo, Y. Wang, and T. Li, "The integrated scheduling optimization for container handling by using driverless electric truck in automated container terminal", *Sustainability,* vol. 15, no. 6, p. 5536, 2023. [http://dx.doi.org/10.3390/su15065536]

[9] S. Venkatesan, "A recommender system based on matrix factorization techniques using collaborative filtering algorithm", *Neuroquantology,* vol. 21, no. 5, pp. 864-872, 2023. [http://dx.doi.org/10.48047/nq.2023.21.5.NQ222079]

[10] R. Widayanti, M. Chakim, C. Lukita, U. Rahardja, and N. Lutfiani, "Improving recommender systems using hybrid techniques of collaborative filtering and content-based filtering", *J. Applied. Data Sci.,* vol. 4, no. 3, pp. 289-302, 2023. [http://dx.doi.org/10.47738/jads.v4i3.115]

[11] Y. Wang, W. Ma, M. Zhang, Y. Liu, and S. Ma, "A survey on the fairness of recommender systems", *ACM Trans. Inf. Syst.,* vol. 41, no. 3, pp. 1-43, 2023. [http://dx.doi.org/10.1145/3547333]

[12] A. Ibrahim, E-S.M. El-Kenawy, M.M. Eid, A.A. Abdelhamid, M. El-Said, A.H. Alharbi, D.S. Khafaga, W.A. Awad, R.Y. Rizk, N. Bailek, and M.A. Saeed, "A recommendation system for electric vehicles users based on restricted Boltzmann machine and WaterWheel plant algorithms", *IEEE Access,* vol. 11, pp. 145111-145136, 2023. [http://dx.doi.org/10.1109/ACCESS.2023.3345342]

[13] D. Wang, R. Zhang, B. Qiu, W. Chen, and X. Xie, "Drop-and-pull container drayage with flexible assignment of work break for vehicle drivers", *Comput. Oper. Res.,* vol. 162, 2024.106475 [http://dx.doi.org/10.1016/j.cor.2023.106475]

[14] W. Tan, X. Yuan, X. Zhang, and J. Wang, "An enhanced adaptive large neighborhood search for fatigue-conscious electric vehicle routing and scheduling problem considering driver heterogeneity", *Expert Syst. Appl.,* vol. 218, 2023.119644 [http://dx.doi.org/10.1016/j.eswa.2023.119644]

[15] "An effective matheuristic approach for robust bus driver rostering with uncertain daily working hours", In: A. Nourmohammadzadeh, and S. Voß, *Computational Logistics.,* Springer: Cham, 2023. [http://dx.doi.org/10.1007/978-3-031-43612-3_23]

[16] Y. Gao, and Y.E. Ge, "Integrated scheduling of yard cranes,

external trucks, and internal trucks in maritime container terminal operation", *Marit. Policy Manage.,* vol. 50, no. 5, pp. 629-650, 2023. [http://dx.doi.org/10.1080/03088839.2022.2135177]

[17] B.A. Weerasinghe, H.N. Perera, and X. Bai, "Optimizing container terminal operations: A systematic review of operations research applications", *Marit. Econ. Logist.,* vol. 2023, 2023. [http://dx.doi.org/10.1057/s41278-023-00254-0]

[18] K. Mili, and M. Gassara, "Multiple straddle carrier routing problem", *J. Marit. Res,* vol. 12, no. 2, p. 63, 2017.

[19] K. Mili, "Solving the straddle carrier routing problem using Six Sigma methodology", *Int. J. Process. Manag. Benchmark.,* vol. 7, no. 3, pp. 371-396, 2017. [http://dx.doi.org/10.1504/IJPMB.2017.084909]

[20] K. Mili, "Dynamic container relocation problem", *J. Marit. Res,* vol. 21, no. 1, pp. 22-29, 2023.