WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Research on Optimization of Warehouse Operation using integrated Planning Systems

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A B S T R A C T

The demand for efficient and agile warehouse operations has intensified in response to the accelerating growth of global supply chains and e-commerce. However, many enterprises continue to operate under fragmented scheduling mechanisms, which often lead to inefficient use of resources and increased operational delays. This paper proposes a hybrid optimization framework that integrates the Genetic Algorithm (GA) and Adaptive Threshold-based Scheduling (ATS) to address such inefficiencies. GA is employed to determine optimal job sequences, while ATS refines the plan in real-time based on operational thresholds and unexpected disturbances. Experimental analysis demonstrates that this combined approach significantly reduces vehicle waiting time, enhances equipment utilization, and streamlines material flow. The results advocate for the broader adoption of intelligent, integrated scheduling systems in complex warehousing environments.

Keywords: warehouse scheduling, optimization, Genetic Algorithm, real-time planning, threshold-based scheduling

1. Introduction

Vietnam's warehousing sector has witnessed an average growth rate exceeding 9.5% annually over the past five years, driven by cross-border trade and digital commerce (Nguyen & Pham, 2023). As warehouse floor area expands to surpass 4 million square meters nationwide, the need for technological transformation in warehouse operations becomes paramount. Notably, storage and handling costs can constitute up to 35% of total logistics expenditure in developing countries (Rai et al., 2019).

One of the most critical inefficiencies arises in inbound and outbound dock scheduling, where manual or static planning methods fail to cope with dynamic workflows, resulting in bottlenecks and underutilization of assets. In this context, the integration of advanced planning techniques such as evolutionary algorithms and real-time control strategies offers promising opportunities for performance improvement.

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2. Literature Review

The Genetic Algorithm (GA) has long been recognized for its efficacy in solving NP-hard scheduling problems due to its population-based search mechanism and capacity for global optimization (Deb, 2001). In warehouse management, GA has proven useful in determining optimal job or vehicle sequences under multiple constraints (Qin et al., 2020). However, it exhibits limitations in environments where real-time adaptability is required, as it primarily yields static plans.

To enhance real-time responsiveness, Adaptive Threshold-based Scheduling (ATS)—a dynamic heuristic method—has been introduced. This approach adjusts operational priorities based on system states such as arrival time deviations, resource saturation, and inventory thresholds (Zhou & Li, 2022). Empirical studies have shown that ATS can decrease processing delays by up to 33% compared to conventional queue-based algorithms like FCFS and SPT (Huang et al., 2023).

3. Research Hypotheses

H1: Genetic Algorithms improve baseline scheduling efficiency in warehouse operations.

H2: Adaptive Threshold-based Scheduling enhances real-time responsiveness and reduces process disruption.

H3: A combined GA + ATS model outperforms single-algorithm approaches in both performance metrics and operational adaptability.

3.1. Solution Design

The Genetic Algorithm is employed in the first phase to derive an optimal sequence of tasks (vehicle handling, dock assignments, order fulfillment). GA is well-suited for warehouse scheduling due to its robustness in navigating large combinatorial spaces and handling multiple conflicting objectives such as cost, time, and resource constraints (Goldberg, 1989; Zhang et al., 2021).

Each chromosome encodes a complete schedule, represented as a permutation of task identifiers (e.g., vehicle IDs or order batches). Gene positions correspond to sequence slots, and gene values indicate task priorities or dock assignments. The following operators are defined:

Selection: Tournament selection is applied to promote fitter chromosomes while maintaining genetic diversity (Whitley, 1994).

Crossover: Order crossover (OX) is utilized to preserve relative task sequences.

Mutation: Swap mutation ensures the exploration of alternative paths and avoids local minima.

Fitness Function: The function is multi-objective and normalized as follows:

$$Fitness(S) = \frac{1}{\propto_1 \mathrm{W(S)} + \propto_2 \mathrm{M(S)} + \propto_3 \mathrm{C(S)}}$$

The algorithm iterates until a convergence threshold is met, such as no improvement over 50 generations or a maximum of 200 iterations. The final output is a static, optimized baseline schedule under ideal assumptions. According to Mitrovic-Minic and Krishnamurti (2001), GA-based frameworks can achieve scheduling efficiency gains of 20–30% in logistics systems, especially in dock door assignment and task batching.

While GA provides an optimal starting point, its offline nature limits adaptability in volatile environments. To compensate, we implement ATS in the second phase as a real-time supervisory controller. ATS operates through event-driven triggers and threshold policies, dynamically modifying task sequences based on updated system states.

Key ATS mechanisms include:

Trigger Events: Late vehicle arrivals, equipment downtime, inventory overflow, or emergency order injections.

Threshold Parameters:

- Maximum Inventory Time (MIT): Tasks are rescheduled if product dwell time exceeds threshold.
- Dock Waiting Threshold (DWT): Triggers reordering if dock queue exceeds a pre-defined level
- Resource Load Factor (RLF): Controls reallocation when labor or forklift usage surpasses safe limits.

Upon event detection, ATS re-evaluates task priority using a weighted scoring function:

Priority $(T_i)=\beta_1 U_i+\beta_2 L_i+\beta_3 D_i$

Where Ui: urgency, Li: lateness, and Di: downstream impact. The system applies rescheduling only within a localized scope (e.g., next 5 tasks), thereby maintaining global consistency from GA while enabling agile correction. This design reflects principles of hybrid control systems in manufacturing, where offline optimization is augmented by real-time dispatching rules (Herrmann & Delalande, 2019).

3.2. Model Development

Sets:
V: Vehicles, D: Dock doors, T: Time periods, R: Resource types, Ov: Tasks assigned to vehicle v

Parameters:

Estimated Time of Arrival (ETA), Task duration, Dock capacity, Resource requirement matrix, Priority levels, Maximum Idle Time (MIT)

Decision Variables:

Binary dock assignment variable, task start/end time variables, sequence variables

Objective Function:

$\min Z=\alpha_1 W+\alpha_2 M+\alpha_3 C$

Where:
W: Total vehicle waiting time

M: Makespan (daily span of operations)

C: Operational cost

Weights αi are assigned based on business priorities.

4. Case Study: Bach Dang Warehouse Simulation

A pilot simulation was conducted at a 120 m² warehouse managed by Bach Dang Group, specializing in construction materials. Two operational scenarios were compared.

Scenario A: Baseline operations using manual scheduling.

Scenario B: Optimized scheduling using the proposed GA+ATS system.

Table 1 - Key Results Over a Simulated 8-Month Period:

KPI	Unit	Baseline	Optimized	Improvement
Daily Operating Span	Hours	11.5	8.3	27.8%
Vehicle Waiting Time	Minutes	52	30.6	41.2%
Order Throughput	Order/day	38	54	42.1%
Equipment Utilization	%	62	84	35.5%
Dock Congestion Level	-	High	Moderate	Pass

5. Conclusion

This research validates that combining evolutionary computation with real-time adaptive scheduling provides a robust solution for modern warehouse operations. The proposed GA+ATS framework significantly reduces inefficiencies in complex, high-throughput environments. While promising, further research should explore machine learning techniques for parameter tuning and test this model across diverse industries such as cold chain logistics and retail fulfillment centers. The integration of GA and ATS yields a synergistic improvement in warehouse scheduling. While GA lays out a globally optimized baseline, ATS responds to deviations and disturbances with threshold-triggered adjustments, creating a dynamic yet stable workflow. The case study shows that this method not only increases throughput and reduces idle time, but also supports operational resilience—an increasingly important trait in volatile logistics environments.

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