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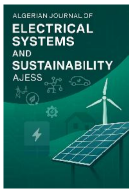

Energy-Efficient Design and Control of AS/RS for Industry 4.0

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Abstract

The evolution of Automated Storage and Retrieval Systems (AS/RS) into intelligent, energy-aware cyber-physical systems marks a turning point in intralogistics. This paper presents a structured review of modeling, optimization, and control strategies for AS/RS, focusing on the convergence of kinematic performance, artificial intelligence (AI), and carbon reduction objectives. We first revisit foundational travel-time and retrieval-time models before highlighting how recent advances integrate simulation, metaheuristics, and reinforcement learning for adaptive scheduling. AS/RS are then analyzed as cyber-physical systems enabled by digital twins, supporting real-time decision-making and energy management. Particular attention is given to energy-saving strategies, including regenerative hardware, AI-based routing, and sustainable layout configurations. Finally, the paper outlines key research challenges—interoperability, AI robustness, and system-level sustainability—and proposes future directions to close the loop between design, operation, and environmental performance. By synthesizing over 40 recent studies, this work provides a comprehensive framework for designing next-generation AS/RS aligned with Industry 4.0 and low-carbon logistics goals.

Keywords

AS/RS, Energy Efficiency, Smart warhousing, Losgistics 4.0, Indsutry 4.0

1. Introduction

The warehousing landscape is undergoing a profound transformation, driven by converging demands for speed, scalability, and sustainability:

- Speed: Same-day delivery expectations push retailers to pick, pack, and ship within tight windows of 20–60 minutes—challenging the limits of traditional manual systems.
- Scale: The ongoing expansion of e-commerce, projected to grow at 11% CAGR, introduces SKU proliferation and seasonal volatility that often overwhelm conventional conveyor-based setups.
- Sustainability: Global decarbonization goals, including Scope 2 emission targets from the EU and IEA, demand energy traceability and carbon-conscious operations across all intralogistics processes.

Automated Storage and Retrieval Systems (AS/RS) address many of the speed and scale requirements by delivering high-density storage, fast retrieval, and real-time order tracking. However, they have historically neglected energy optimization and carbon impact. Earlier travel-time models [1] assumed unlimited energy input, treating electricity simply as a cost rather than a constraint or design factor.

Recent technological advances—such as regenerative drives, supercapacitor buffering, and AI-enabled scheduling—raise an urgent and timely question:Can we co-optimize cycle time and energy consumption without sacrificing performance?

This article addresses that question through a structured and integrated approach:

- Section 2 provides a comprehensive literature review of over four decades of AS/RS research, including foundational analytical models, design optimization strategies, control systems, and energy-aware frameworks.
- Section 3 places AS/RS in the context of Industry 4.0, examining their evolution into cyber-physical systems and exploring enabling technologies such as digital twins, IoT-based control, and carbon-aware warehousing.
- Sections 4–6 develop and evaluate a unified architecture combining analytical modeling, digital twins, and deep reinforcement learning (DRL) to simultaneously minimize cycle time and energy consumption.
- Section 7 discusses system-level energy savings and sustainability strategies.
- Section 8 reflects on current challenges and future research directions.
- Section 9 concludes by highlighting the contributions and outlining a path toward resilient, low-carbon AS/RS operations.

2. Structured Literature Review

The literature on Automated Storage and Retrieval Systems (AS/RS) spans more than four decades, evolving from basic analytical models to advanced cyber-physical implementations. This section reviews the foundational contributions and recent developments across four major domains: analytical modeling, design optimization, AI-based operational control, and energy-aware strategies.

2.1 Analytical Foundations

The earliest models focused on quantifying travel time in AS/RS to optimize throughput. The seminal work by Bozer and White [1] introduced time models for unit-load crane-based systems, identifying the square-in-time layout as optimal. Sari et al. [2] and Ghomri& Sari [3] and Ghomri et al. [4] extended these concepts to flow-rack AS/RS, accounting for class-based storage and dual cycles. Continuous modeling approaches were also proposed to evaluate performance under varying command and density conditions [5].

Kouloughli et al. [6] introduced multi-agent coordination for reducing retrieval times in gravity-fed flow-rack systems, while Bessenouci et al. [7] demonstrated metaheuristic control integration. Roodbergen and Vis [8] offered a comprehensive classification of AS/RS models, and Mostofi&Erfanian [9] reviewed developments specific to multi-shuttle systems.

2.2 Design Optimization

Design optimization methods range from simulation to metaheuristics. Fandi et al. [10] applied genetic algorithms to optimize multi-aisle, multi-shuttle AS/RS dimensions. Hamzaoui et al. [11] focused on bidirectional flow-rack systems, co-optimizing machine design and storage layout. Ekren et al. [12] developed a performance estimation tool accounting for cycle time variance and energy consumption.

Simulation-based approaches such as those by De Maio et al. [13] and Urnauer et al. [14] helped refine design parameters, while Cunkas& Ozer [15] tackled location assignment optimization in dual-shuttle systems. Energy efficiency models for mini-load AS/RS were developed by Lerher et al. [16], enabling sustainable design evaluation during early planning stages.

2.3 Operational Control and AI

The rise of artificial intelligence has transformed AS/RS control. Bessenouci et al. [7] applied Tabu Search to real-time sequencing, marking early integration of intelligent heuristics. More recently, Zhao et al. [17] proposed resilient AI-based control under sensor and actuator attacks. Digital twins, as discussed by Park et al. [18], and compliance-focused architectures by Zhang et al. [19], support predictive control and fault tolerance.

Liu et al. [20] reviewed AI integration into cyber-physical logistics systems, while Hussein & Moharram [21] developed MADTwin for multi-agent coordination in smart warehouses. UAV-based traceability systems proposed by Fernández-Caramés et al. [22], exemplify the convergence of AI, IoT, and automation in advanced AS/RS environments.

2.4 Energy-Aware Studies

As sustainability takes center stage, energy optimization in AS/RS has become critical. Bartolini et al. [23] offered a systematic review of green warehousing practices. Rizqi et al. [24], [25], [26] developed simulation-optimization models for energy-aware AS/RS layout and operation, emphasizing energy harvesting and I/O point design.

Liu et al. [27] proposed an energy model for shuttle-based systems considering dynamic motion and braking. Bruckmann et al. [28] focused on wire-based energy-efficient AS/RS, while Putra et al. [29] proposed an energy recovery framwork for AS/RS. On the other hand, Hsu et al. [30] optimized crane scheduling to reduce electricity use. Tubis&Rohman [31] and Werbińska-Wojciechowska et al. [32] reviewed CPS and digital twin roles in sustainable operations.

Edouard et al. [33] addressed AS/RS in urban warehousing for CO_2 reduction, while Tonelli et al. [34] emphasized CPS-based coordination in supply chains. Moufaddal et al. [35] integrated energy metrics in CPS warehouse architecture. Zhang [36] explored IoT-driven logistics in CPS environments, and Oks et al. [37] provided a structured categorization of CPS in Industry 4.0. Suárez-Riveros et al. [38] and Xu et al. [39] rounded out the energy-aware landscape with studies on smart supply chains and compound operation scheduling.

3. AS/RS within the Industry 4.0 Paradigm

Automated Storage and Retrieval Systems (AS/RS) are evolving into integral components of Industry 4.0, where automation, connectivity, and sustainability converge to redefine intralogistics. Far from being isolated electromechanical units, modern AS/RS function as cyber-physical systems (CPS) that bridge the digital and physical domains [35], [18], [36]. They integrate real-time sensing, intelligent decision-making, and seamless communication across the warehouse environment.

3.1 From Automation to Cyber-Physical Systems

The transformation of AS/RS into CPS enables them to interact continuously with their environment through sensors, actuators, and embedded processors. This allows dynamic adjustments based on operational data, improving system responsiveness and adaptability. The work of Tonelli et al. [34] emphasizes how CPS frameworks restructure traditional warehousing processes, while Park et al. [18] demonstrate the embedding of AS/RS into broader Industry 4.0 architectures. Moufaddal et al. [35] propose an intelligent warehouse management system where AS/RS operate as CPS nodes within a multi-layered architecture.

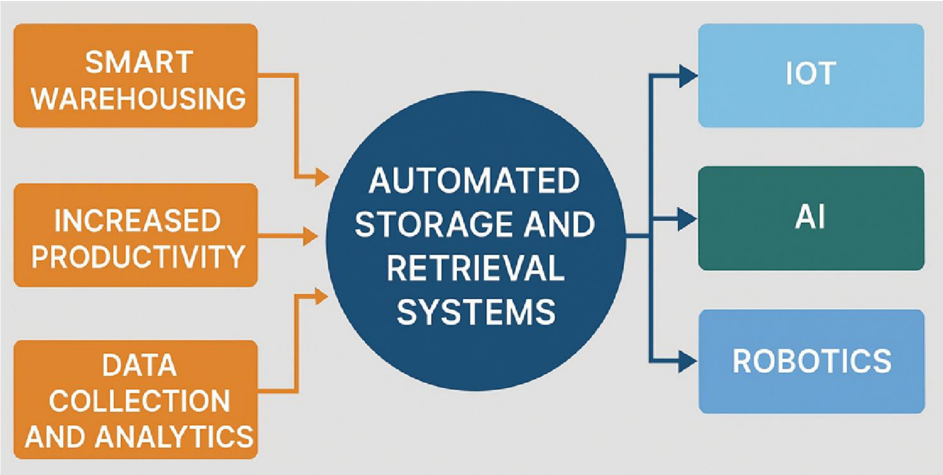


Fig. 1: Cyber-physical role of an AS/RS, showing the sensor → edge → cloud data stack enabling closed-loop optimization.

3.2 The Rise of Digital Twins

One of the key enablers of AS/RS evolution is the implementation of digital twins—virtual models that mirror the state and behavior of the physical system. These digital replicas facilitate advanced analytics, predictive maintenance, and real-time control. Zhang et al. [19] introduced a digital twin framework that ensures adaptive compliance in smart warehouse logistics, while Hussein and Moharram [21] developed MADTwin, a multi-agent architecture for simulating warehouse dynamics. Werbińska-Wojciechowska et al. [32] reviewed the use of digital twins for operation and maintenance optimization, highlighting their relevance in transportation and intralogistics systems.

3.3 Interoperability and Edge Intelligence

Interoperability is critical for AS/RS systems operating in a connected warehouse ecosystem. These systems must exchange data seamlessly with other machines and enterprise platforms. Technologies such as edge computing and industrial IoT (IIoT) allow AS/RS to process and act upon data locally, reducing latency and enhancing responsiveness. Liu et al. [20] review how AI and CPS integration enables intelligent logistics networks, while Zhang [36] presents a smart logistics path that combines IoT and CPS to support decentralized control and adaptive operations in warehouse environments.

3.4 Energy Efficiency and Sustainable Design

In addition to performance and integration, AS/RS must address sustainability challenges. Energy-efficient design, carbon-aware scheduling, and intelligent resource management are now essential components of modern intralogistics. Bartolini et al. [23] conducted a systematic literature review on green warehousing strategies, identifying AS/RS as a cornerstone technology for energy optimization. Edouard et al. [33] highlight the role of AS/RS in supporting urban sustainability goals by enabling compact, automated, and low-energy storage solutions within urban distribution centers.

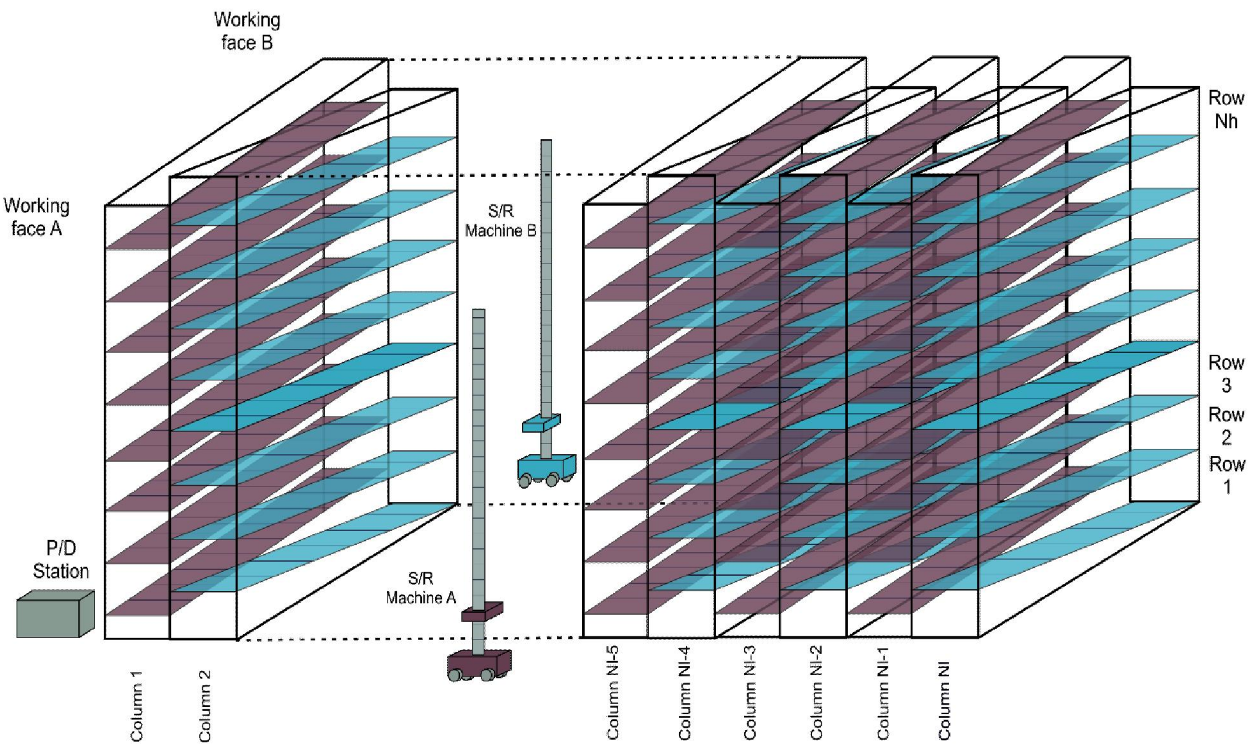


Fig. 2: Bidirectional flow rack AS/RS schematic

4 Analytical Modeling of Time and Energy

4.1 Time Models

To illustrate our investigations let us present the travel times model of the bidirectional flow rack AS/RS represented in Figure 2. In this setup, storage racks are accessible from both sides, referred to as Working Face A and Working Face B. Each face is served by a dedicated Storage and Retrieval machine, allowing simultaneous access and improving throughput efficiency.

Items are loaded from the P/D stations and move into the racks via gravity conveyors,

This bidirectional design supports higher throughput and is particularly effective in high-demand, high-density warehousing environments, where access speed and storage depth are critical factors.

Analytical travel time models developed for bidirectional flow rack AS/RS system [11], [40] are presented as follows:

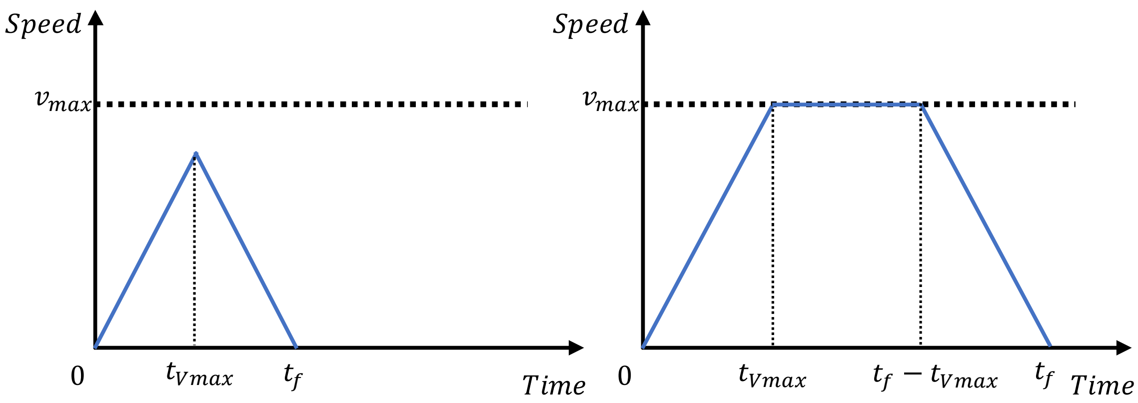
Storage
$$ESC^C = \frac{T}{2}\left(\frac{b^2}{3}+1\right) \tag{1}$$

Retrieval
$$ERC^C = \frac{T}{\rho M}\left(\frac{b^2}{3}+1\right)\left(\frac{2\rho M-1}{2}\right)+(\rho M-1)t'_p \tag{2}$$

Dual cycle in adjacent bin
$$EDC1^C = \frac{T}{2\rho M}\left(\frac{b^2}{3}+1\right)(2\rho M-1)+\left(\frac{2\rho^2M^2-1}{2\rho M}\right)t'_p \tag{3}$$

Dual cycle in different bins
$$EDC2^C = \frac{T}{2\rho M}\left(\frac{4}{3}+\frac{b^2}{2}-\frac{b^3}{30}\right)+(2\rho M-1)+(\rho M-1)t'_p \tag{4}$$

The models represented by equations (1-4) allow precise evaluation of performance under various command strategies and density conditions, making them essential for designing and controlling efficient bidirectional AS/RS systems. However, they do not consider acceleration and deceleration of the S/R machine which make them not suitable for energy investigations. Hence, let consider more realistic travel time models by incorporating the acceleration and deceleration phases of Storage and Retrieval (S/R) machines.



Case 1

$$v(t) = \begin{cases} at & t \in [0; t_{Vmax}] \\ -a(t-t_f) & t \in [t_{Vmax}; t_f] \end{cases} \tag{5}$$

Case 2

$$v(t) = \begin{cases} at & t \in [0; t_{Vmax}] \\ v_{max} & t \in [t_{Vmax}; t_f - t_{Vmax}] \\ -a(t-t_f) & t \in [t_f - t_{Vmax}; t_f] \end{cases} \tag{6}$$

Fig. 3: speed profiles of S/R machines in AS/RS

We examine two cases as shown in figure 3.

Case 1 (left graph): The machine never reaches maximum speed. Instead, it accelerates to a peak speed before immediately decelerating. The speed profile is triangular.

Case 2 (right graph): The machine reaches and maintains the maximum speed for a period before decelerating. This results in a trapezoidal speed profile.

These models provide a more accurate estimation of travel time compared to constant-speedassumptions, especially for short distance movements within AS/RS systems. Integrating acceleration effects is essential for energy optimization, motor sizing, and precise scheduling in automated warehousing.

The following equations show detailed formulas for calculating storage and retrieval times in AS/RS systems while considering acceleration and deceleration of machines. Equation (7) estimates storage time, and equation (8) estimates retrieval time, including the effect of machine speeds, accelerations, and system dimensions like height and depth. It should be noted that the equations presented in this paper are valid only for the case;$t_h \leq t_v \leq t_H \leq t_V$ all other possible cases can be found in the PhD Thesis of M.A. Hamzaoui [40].

$$ESC^1 = -\frac{a_V v_H^5}{15a_H^4 HV} + \frac{V}{2v_V} + \frac{v_V}{a_V} + \frac{v_V H}{2a_H V} + \frac{v_V H^2}{6v_H^2 V} + \frac{v_H^2 v_V}{2a_H^2 V} + \frac{v_H^4 v_V}{6a_H^3 HV} - \frac{v_V^2 H}{2a_V v_H V} - \frac{v_H v_V^2}{a_H a_V V} - \frac{v_H^3 v_V^2}{2a_H^2 a_V HV} + \frac{v_V^3}{2a_V^2 V} + \frac{2v_H^2 v_V^3}{3a_H a_V^2 HV} - \frac{v_H v_V^4}{3a_V^3 HV} \tag{7}$$

$$ERC^1 = \left(2 - \frac{1}{M'}\right)\left(-\frac{a_V v_H^5}{15a_H^4 HV} + \frac{V}{2v_V} + \frac{v_V}{a_V} + \frac{v_V H}{2a_H V} + \frac{v_V H^2}{6v_H^2 V} + \frac{v_H^2 v_V}{2a_H^2 V} + \frac{v_H^4 v_V}{6a_H^3 HV} - \frac{v_V^2 H}{2a_V v_H V} - \frac{v_H v_V^2}{a_H a_V V} - \frac{v_H^3 v_V^2}{2a_H^2 a_V HV} + \frac{v_V^3}{2a_V^2 V} + \frac{2v_H^2 v_V^3}{3a_H a_V^2 HV} - \frac{v_H v_V^4}{3a_V^3 HV}\right) + (M' - 1){t'}_p \tag{8}$$

These models give a more realistic and precise view of system performance compared to simple constant-speed assumptions.

While the expression (9) presents the extended travel time model for dual-cycle operations in adjacent bins, while factoring in acceleration and deceleration of storage and retrieval machines.

$$\begin{aligned} EDC^1 = \left(1 - \frac{1}{2M'}\right)\Bigg(& -\frac{2a_V v_H^5}{5a_H^4 HV} + \frac{4a_V^2 v_H^7}{105a_H^6 HV^2} + \frac{4a_V v_H^7}{105a_H^5 H^2 V} - \frac{4a_V^2 v_H^9}{315a_H^7 H^2 V^2} + \frac{4V}{3v_V} + \frac{3v_V}{a_V} + \frac{5v_V H}{3a_H V} + \frac{H^2 v_V}{2v_H^2 V} \\ & + \frac{2v_H^2 v_V}{a_H^2 V} + \frac{v_H^4 v_V}{a_H^3 HV} + \frac{v_H^6 v_V}{6a_H^4 H^2 V} - \frac{v_V^2 H^3}{30V^2 v_H^3} - \frac{v_V^2 H^2}{6a_H v_H V^2} - \frac{5v_V^2 H}{3a_V v_H V} - \frac{v_H v_V^2 H}{3a_H^2 V^2} - \frac{4v_H v_V^2}{a_H a_V V} - \frac{v_H^3 v_V^2}{3a_H^3 V^2} \\ & - \frac{3v_H^3 v_V^2}{a_H^2 a_V HV} - \frac{v_H^5 v_V^2}{6a_H^4 HV^2} - \frac{2v_H^5 v_V^2}{3a_H^3 a_V H^2 V} - \frac{v_H^7 v_V^2}{30a_H^5 H^2 V^2} + \frac{2v_V^3 H}{3a_H a_V V^2} + \frac{2v_V^3}{a_V^2 V} + \frac{v_V^3 H^2}{6a_V v_H^2 V^2} + \frac{v_H^2 v_V^3}{a_H^2 a_V V^2} \\ & + \frac{4v_H^2 v_V^3}{a_V^2 a_H HV} + \frac{2v_H^4 v_V^3}{3a_H^3 a_V HV^2} + \frac{4v_H^4 v_V^3}{3a_H^2 a_V^2 H^2 V} + \frac{v_H^6 v_V^3}{6a_H^4 a_V H^2 V^2} - \frac{v_V^4 H}{3a_V^2 v_H V^2} - \frac{v_H v_V^4}{a_H a_V^2 V^2} - \frac{42v_V^4}{a_V^3 HV} \\ & - \frac{v_H^3 v_V^4}{a_H^2 a_V^2 HV^2} - \frac{4v_H^3 v_V^4}{3a_H a_V^3 H^2 V} - \frac{v_H^5 v_V^4}{3a_H^3 a_V^2 H^2 V^2} + \frac{v_V^5}{3a_V^3 V^2} + \frac{8v_H^2 v_V^5}{15a_H a_V^3 HV^2} + \frac{8v_H^2 v_V^5}{15a_V^4 H^2 V} + \frac{4v_H^4 v_V^5}{15a_H^2 a_V^3 H^2 V^2} \\ & - \frac{8v_H^2 v_V^7}{105a_V^5 H^2 V^2}\Bigg) + (M' - 1){t'}_p \end{aligned} \tag{9}$$

Although the formula appears complex, it enables highly accurate performance estimation in dynamic systems by integrating all movement phases and machine parameters.

4.2 Energy Models

To illustrate energy models for AS/RS, let us present the work performed by Ekren et al. [12]. The authors propose an analytical tool that estimates key performance indicators (KPIs) related to time, variance, and energy consumption in a shuttle-based Automated Storage and Retrieval System (AS/RS). The model is designed to optimize system performance by evaluating the efficiency of the shuttle operations, energy consumption, and the impact of system layout.

4.2.1 Key Components of the Model:

*Cycle Time Calculation:*The model calculates the average cycle time of the shuttle, which includes the time taken for loading and unloading the goods, as well as the movement time between storage locations. It takes into account parameters like the length of the travel path, shuttle speed, acceleration, and the number of aisles and levels in the AS/RS.

*Variance in Cycle Time:*The model also estimates the variance in cycle time, which is critical for assessing the consistency and reliability of the AS/RS operations. The variance helps in understanding the fluctuation in retrieval times, which directly affects the overall system performance.

*Energy Consumption:*A key aspect of this model is the inclusion of energy consumption estimations for the shuttle. The system takes into account the dynamic energy consumption required for shuttle movement, including acceleration, deceleration, and braking phases. Energy consumption is also affected by regenerative braking systems, which allow the shuttle to recover energy during braking. The model incorporates these regenerative aspects to provide a more accurate energy profile of the AS/RS.

*Energy Recovery:*The model simulates the energy recovery during braking phases, which is a critical component for improving the system's energy efficiency. The energy recovered is fed back into the system, reducing the total energy required for shuttle movements. The model optimizes the operational sequencing to maximize regenerative energy recovery.

*Performance Optimization:*The tool helps in optimizing the configuration of the shuttle-based AS/RS by adjusting parameters such as aisle length, shuttle speed, and number of levels. The goal is to minimize the total energy consumption while maintaining high throughput and minimizing cycle time variance.

4.2.2 Model Application:

This analytical tool is particularly useful for AS/RS designers and managers who need to assess and optimize system performance, especially from an energy efficiency perspective. It provides insights into how layout choices and operational parameters (like shuttle speeds and acceleration rates) affect the overall system's performance. By applying this model, operators can achieve a more sustainable and cost-efficient system, reducing energy consumption and operating costs without compromising performance.

5. Design and Operational Optimization

Optimizing AS/RS design and operation is essential to meet performance, scalability, and energy efficiency goals. Recent studies distinguish between static design optimization (layout, configuration) and dynamic operational optimization (scheduling, routing, energy management). Hybrid approaches combining simulation, metaheuristics, and artificial intelligence have emerged as powerful tools for achieving holistic improvements.

5.1 Static Design Optimization

The static design problem in AS/RS concerns the selection of layout parameters such as rack depth, number of aisles, storage policies, and shuttle configurations to minimize travel time and energy consumption. Genetic algorithms (GA), integer programming, and simulation-based evaluation are frequently used in this context.

Fandi et al. [10] applied a GA-based method to optimize the dimensions of a multi-shuttle AS/RS, demonstrating significant gains in retrieval time. Hamzaoui et al. [11] extended this work to bidirectional flow-rack configurations, integrating dual-cycle models into the layout design process. Lerher et al. [16] developed an analytical energy-efficiency model for mini-load AS/RS to guide early-stage system sizing, while Cunkas and Ozer [15] proposed a dual-shuttle layout optimized through location assignment heuristics.

Moreover, De Maio et al. [13] and Urnauer et al. [14] validated static configuration choices via discrete-event simulation, assessing throughput and buffer utilization in industrial scenarios. These studies emphasize the importance of matching AS/RS architecture with workload patterns and energy constraints.

5.2 Dynamic Operation

While static design sets the foundation, dynamic operational optimization determines real-world system efficiency. Classical approaches such as nearest-neighbor or random retrieval policies fail to adapt under load variability or energy constraints. In contrast, intelligent control policies can dynamically respond to order streams, congestion, and machine availability.

Bessenouci et al. [7] implemented Tabu Search for sequencing commands in flow-rack AS/RS, outperforming rule-based scheduling. More recently, Liu et al. [20] demonstrated the power of AI integration in cyber-physical logistics systems, enabling predictive adjustments based on system state. Hussein and Moharram [21] further extended this through MADTwin, where multi-agent models dynamically schedule operations with coordination.

Reinforcement learning also plays a key role. Zhao et al. [17] proposed a resilient control framework for CPS-based systems, allowing real-time adaptation under actuator or sensor disruption. These models ensure stability while maintaining throughput and energy performance in fluctuating environments.

Additionally, Xu et al. [39] introduced a scheduling optimization framework for compound operations in autonomous vehicle-based AS/RS. Their work addressed the complexity of synchronizing multiple handling tasks in double-deep storage systems, using symmetry-based models to improve overall system flow and reduce congestion.

These contributions highlight that robust, adaptive, and predictive scheduling strategies are essential to fully leverage the operational flexibility of modern AS/RS systems.

5.3 Hybrid Approaches and Energy Management

Hybrid methods combine simulation, AI, and metaheuristics to jointly optimize retrieval time, energy consumption, and system robustness. Ekren et al. [12] proposed a performance estimation tool that captures time, variance, and energy indicators in shuttle-based AS/RS. Their model serves as a feedback mechanism to adjust both static and dynamic parameters.

Rizqi et al. [24], [25], [26] introduced multi-objective simulation-optimization frameworks that integrate energy harvesting, optimal I/O point placement, and storage assignment for sustainable AS/RS design. Their models highlight trade-offs between throughput, energy, and mechanical stress.

Energy management also benefits from digital twin integration. Zhang et al. [19] and Moufaddal et al. [35] proposed CPS architectures where real-time data from physical assets inform decision-making. By combining real and simulated feedback, these systems optimize both operations and energy profiles.

Bruckmann et al. [28] demonstrated how mechanical redesign (e.g., wire-based handling) can drastically improve energy efficiency, especially when coupled with intelligent sequencing. Hsu et al. [30] applied simulation-based optimization to crane scheduling, achieving reduced electricity consumption during high-density retrieval phases.

These studies confirm that hybrid optimization—combining data, simulation, and intelligent control—offers the most promising path toward sustainable, high-performance AS/RS systems.

6. AI Control Architecture with Digital Twin

The convergence of Artificial Intelligence (AI) and Digital Twin (DT) technologies has revolutionized the control of Automated Storage and Retrieval Systems (AS/RS), enabling them to operate autonomously, adaptively, and energy-efficiently. AS/RS are increasingly embedded within cyber-physical systems (CPS), where virtual models continuously mirror physical operations to optimize performance in real time [35], [19].

6.1 Multi-Layered Architecture

Modern AS/RS control systems follow a multi-layered architecture, integrating field data acquisition, edge intelligence, and enterprise-level supervision:

- Field Layer: Includes IoT sensors monitoring shuttle position, velocity, load status, and energy consumption. These sensors generate high-frequency data streams essential for adaptive control [36], [20].
- Edge Layer: Edge computing units, often GPU-enabled (e.g., NVIDIA Jetson), run lightweight AI models to make ultra-fast control decisions. Zhang [36] and Liu et al. [20] emphasize the importance of localized intelligence to reduce latency and improve responsiveness under dynamic warehouse conditions.
- Digital Twin Layer: The DT provides a synchronized virtual replica of the AS/RS, capable of simulating failure scenarios, predicting system degradation, and testing alternative operational strategies [19], [21], [32]. Hussein & Moharram [21] developed the MADTwin framework, a multi-agent digital twin platform that supports real-time co-simulation of multiple AS/RS components.
- Enterprise Layer: Supervisory systems collect key performance indicators (KPIs), manage exception handling, and interface with external systems such as Warehouse Management Systems (WMS) and Enterprise Resource Planning (ERP).

This layered structure ensures resilience, modularity, and adaptability, and enables predictive control across both individual machines and system-wide operations.

6.2 Deep Reinforcement Learning (DRL) for Control

Deep Reinforcement Learning (DRL) has emerged as a powerful tool for dynamic AS/RS scheduling and routing. Unlike rule-based heuristics, DRL continuously learns from environmental feedback to improve retrieval sequences, energy efficiency, and response to disturbances.

Zhao et al. [17] proposed a DRL-based architecture that remains resilient under actuator and sensor attacks, ensuring robust performance even in uncertain CPS conditions. Fernández-Caramés et al. [22], demonstrated a blockchain-enhanced DRL system with UAV-based inventory scanning, highlighting DRL's potential in large-scale warehouse ecosystems.

The MADTwin platform [21] integrates DRL agents into a digital twin context, enabling AS/RS to learn optimal operational strategies in simulated environments before deployment. This approach accelerates convergence, reduces energy peaks, and enhances safety.

6.3 AI and Energy Optimization

AI contributes significantly to energy-aware decision-making in AS/RS control. By integrating energy models and carbon pricing signals into control objectives, DRL agents can:

- Prioritize retrievals with minimal energy cost,
- Avoid high power peaks,
- Maximizeregenerativebrakingrecovery [12], [28].

Rizqi et al. [24], [26] developed multi-objective simulation-optimization frameworks where AI selects energy-optimal paths and configurations. Their models demonstrate how machine learning can anticipate energy bottlenecks and reconfigure I/O assignment or storage zones in real time.

Moufaddal et al. [35] integrated these features into a CPS control architecture where AI modules coordinate across layers, combining predictive analytics and real-time feedback.

6.4 Security and System Integrity

As AS/RS become increasingly autonomous and connected, cyber-physical security becomes a critical concern. DRL systems must handle incomplete, noisy, or manipulated input. Zhang et al. [19] emphasized the importance of adaptive compliance mechanisms that verify state validity before action. Redundant sensing, anomaly detection, and fallback control strategies are crucial to ensure safety.Werbińska-Wojciechowska et al. [32] reviewed the role of digital twins in system monitoring and integrity validation, demonstrating their value in proactive fault detection and recovery planning.

7. Energy Savings and Sustainability

Energy optimization is no longer a secondary concern in the design and control of Automated Storage and Retrieval Systems (AS/RS). As intralogistics becomes increasingly digital and automated, the need to reduce operational electricity consumption, carbon emissions, and peak power demand is driving innovation at multiple system levels. Recent research integrates mechanical design, regenerative technologies, artificial intelligence (AI), and control architectures to maximize energy efficiency without compromising throughput. Figure 4 outlines the various energy-saving strategies, including regenerative braking, lightweight design, and low-inertia sequencing.

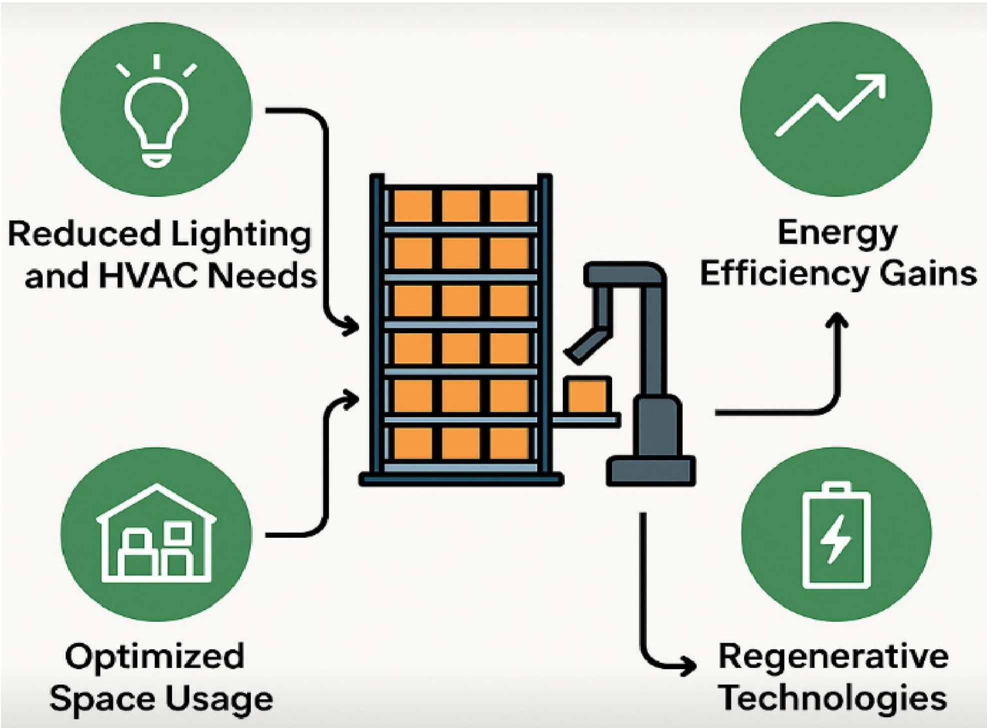


Fig.4: Energy-saving levers for AS/RS systems, showing mechanical, regenerative, and AI-based control strategies to reduce energy consumption.

7.1 Mechanical Design Innovations

At the physical layer, the choice of materials, shuttle weight, and structural layout directly influences energy demand. Lightweight materials, such as carbon fiber or composite frames, reduce the force required for acceleration and lifting. Lerher et al. [16] proposed an analytical model that quantifies the impact of rack dimensions and shuttle mass on energy usage in mini-load AS/RS, supporting energy-aware dimensioning from the design phase.

Bruckmann et al. [28] introduced a wire-based AS/RS architecture that minimizes friction and mass displacement, leading to significant reductions in motor power and thermal losses. These innovations confirm that early-stage mechanical choices have long-term implications on energy consumption and equipment wear.

7.2 Regenerative Systems and Hardware Efficiency

AS/RS are uniquely suited to benefit from regenerative braking, where kinetic energy from deceleration is captured and reused. Ekren et al. [12] modeled energy recovery rates based on acceleration profiles and system inertia, showing that shuttle-based AS/RS can recover up to 30–40% of expended energy during descent or braking.

Rizqi et al. [24], [25] further optimized these configurations by incorporating energy harvesting mechanisms directly into the storage assignment strategy. Their work demonstrates how the placement of heavy items, I/O points, and retrieval routes can influence regenerative potential.

Energy harvesting not only reduces net consumption but also improves power quality by smoothing peak loads. Advanced hardware components like supercapacitors and low-loss drives are now integrated to store and deploy this recovered energy with minimal latency.

7.3 AI-Driven Scheduling and Smart Energy Control

Beyond hardware, significant energy gains can be achieved through smart scheduling algorithms that coordinate task execution based on energy and carbon priorities. Deep Reinforcement Learning (DRL), as explored by Zhao et al. [17] and Moufaddal et al. [35], allows AS/RS systems to learn optimal retrieval sequences that minimize total power draw.

Rizqi et al. [26] introduced a multi-objective optimization model where energy, time, and system load are jointly minimized. The use of digital twins to simulate energy profiles, as proposed by Zhang et al. [19] and Hussein & Moharram [21], enables predictive adjustments to system behavior—shifting intensive actions to off-peak hours or periods of low carbon intensity.

In hybrid systems, AI controllers dynamically adjust routing, load balancing, and idle time strategies, maximizing the recovery of regenerative energy and avoiding unnecessary activation of power-hungry subsystems.

7.4 System-Level Sustainability and Urban Logistics

AS/RS also contribute to sustainability at the warehouse and supply chain level. In dense urban environments, vertical automation reduces the building footprint and supports last-mile logistics. Edouard et al. [33] evaluated AS/RS deployment in urban warehouses and demonstrated reduced CO_2 emissions due to minimized transport distances and better space utilization.

Bartolini et al. [23] emphasized the broader impact of AS/RS in green warehousing, developing a framework for evaluating sustainability metrics including lifecycle emissions, energy intensity, and automation index.

Tonelli et al. [34] connected these innovations to supply chain-wide carbon reduction strategies, showing how CPS-integrated AS/RS systems align with international decarbonization goals.

8. Challenges and Research Directions

As AS/RS evolve into cyber-physical systems within Industry 4.0, new challenges emerge across technical, environmental, and organizational dimensions. While digital twins, AI-based control, and energy-aware design show strong potential, several research gaps and implementation bottlenecks remain.

8.1 Interoperability and System Complexity

A major challenge lies in achieving interoperability between AS/RS and other warehouse components (e.g., AGVs, conveyors, ERP systems). The heterogeneity of devices, protocols, and data models complicates integration. Liu et al. [20] emphasized the need for standardized interfaces and communication frameworks to support plug-and-play automation. Zhang [36] proposed IoT-driven logistics architectures that enable real-time coordination but require robust middleware and edge intelligence.

Cyber-physical systems, as reviewed by Oks et al. [37], face growing architectural complexity. Ensuring synchronization between the physical and digital layers—especially in multi-agent environments—remains nontrivial. Hussein & Moharram [21] addressed this with MADTwin, but scalability and real-time constraints continue to challenge system designers.

8.2 Energy Modeling and Lifecycle Assessment

Although energy-aware models have improved significantly, real-time energy estimation remains a research frontier. Most models rely on simplified or offline parameters. Rizqi et al. [24], [25] highlighted the difficulty of integrating energy recovery dynamics, variable load profiles, and stochastic order flows into optimization frameworks.

Moreover, few studies perform full lifecycle assessments (LCA) of AS/RS installations. Bartolini et al. [23] called for holistic sustainability models encompassing manufacturing, operation, maintenance, and end-of-life phases. Without these, decision-makers lack visibility into long-term environmental impacts.

8.3 AI Robustness and Security

The adoption of AI-based control introduces risks related to model robustness and cyber-physical security. DRL systems may overfit to specific warehouse conditions or fail under sensor drift and communication delays. Zhao et al. [17] demonstrated how actuator and sensor attacks can compromise control, requiring resilient architectures with fallback logic.

Zhang et al. [19] advocated for adaptive compliance mechanisms where AI decisions are validated against physical constraints before execution. Similarly, Werbińska-Wojciechowska et al. [32] stressed the role of digital twins in monitoring system integrity and anticipating failures. However, further work is needed on AI interpretability, fault tolerance, and secure deployment in mission-critical logistics environments.

8.4 Data Availability and Transferability

Another pressing issue is the scarcity of open datasets and benchmarks. Most studies rely on simulated data or proprietary warehouse profiles, limiting result generalization. As noted by Tubis&Rohman [31], reproducibility is a key obstacle to scientific progress in warehouse automation.

In addition, many optimization strategies are developed for specific configurations (e.g., dual-shuttle, mini-load), reducing their transferability. De Maio et al. [13] and Mostofi&Erfanian [9] suggested the development of modular, reconfigurable models that adapt across system scales and use cases.

8.5 Future Research Directions

To address these challenges, several research avenues are recommended:

- Unified modeling frameworks that integrate kinematic, energy, and control variables in both simulation and real-time environments [12], [26].
- Scalable digital twin architectures, including lightweight models for edge deployment and high-fidelity twins for system-wide planning [19], [21].
- Explainable and secure AI systems that can provide human-understandable justifications for decisions, improving operator trust and safety [17], [32].
- Standardized evaluation metrics and benchmark datasets to enable fair comparison across algorithms and system types [31].
- Urban-scale optimization models that account for AS/RS integration into sustainable supply chains and smart city logistics [33], [34].

By addressing these gaps, researchers can unlock the full potential of next-generation AS/RS systems that are not only fast and scalable, but also resilient, explainable, and aligned with environmental goals.

9 Conclusion

Automated Storage and Retrieval Systems (AS/RS) are undergoing a profound transformation as they evolve from deterministic, isolated machines into intelligent cyber-physical systems embedded within the fabric of Industry 4.0. This article has provided a structured overview of the evolution of AS/RS design and control by integrating more than four decades of analytical modeling with the latest advances in artificial intelligence, digital twins, and energy-aware optimization.

The review has shown that traditional analytical models remain valuable for foundational performance estimation, particularly regarding retrieval times and throughput under different configurations. However, modern AS/RS now operate in dynamic, data-rich environments where static models must be supplemented by simulation, metaheuristics, and learning-based approaches. Several studies demonstrated the efficacy of multi-objective optimization and reinforcement learning in adapting to variable workloads, minimizing energy consumption, and improving responsiveness.

The integration of digital twins and AI-based control enables real-time monitoring, fault detection, and energy-aware scheduling. Architectures such as MADTwin and CPS-based frameworks illustrate how AS/RS can self-adapt through interaction between virtual and physical layers. These capabilities are crucial for supporting sustainable and resilient warehouse operations, particularly as energy constraints, carbon targets, and system complexity increase.

Nevertheless, challenges remain. Interoperability across heterogeneous systems, robustness of AI under uncertainty, real-time energy modeling, and the lack of standardized benchmarks hinders widespread deployment. Research must now focus on developing scalable, secure, and explainable AI frameworks, as well as digital twins that support predictive control, lifecycle assessment, and integration into broader supply chain ecosystems.

Ultimately, the convergence of AI, CPS, and sustainability in AS/RS represents a paradigm shift in intralogistics. By closing the loop between system design, operational intelligence, and environmental objectives, next-generation AS/RS can serve not only as productivity enablers but as critical assets for building resilient and low-carbon supply chains.

Appendix – Summary of Research Themes and Associated References

This appendix provides a structured overview of the key research areas addressed in this paper, linking each theme to representative and authoritative references used throughout the article.

Theme	Representative References
Travel Time Modeling in AS/RS	[1] Bozer& White (1984), [2] Sari et al. (2005), [3] Ghomri& Sari (2017), [4] Ghomri et al. (2009), [5] Lehmann &Hußmann (2022) [6] Kouloughli et al. (2018), [9] Mostofi&Erfanian (2018), [40] Hamzaoui (2020)
Design Optimization (Layout, Shuttles, Configuration)	[10] Fandi et al. (2022), [11] Hamzaoui et al. (2024), [13] De Maio et al. (2024), [14] Urnauer et al. (2020), [15] Cunkas&Ozer (2019), [16] Lerher et al. (2014) , [40] Hamzaoui (2020)
Energy Modeling and Harvesting	[12] Ekren et al. (2018), [24] Rizqi et al. (2024), [25] Rizqi et al. (2024), [26] Rizqi et al. (2024), [27] Liu et al. (2021), [28] Bruckmann et al. (2013), [29] Putra et al. (2022), [30] Hsu et al. (2022)
AI-Based Control and Scheduling	[7] Bessenouci et al. (2012), [17] Zhao et al. (2021), [20] Liu et al. (2023), [21] Hussein &Moharram (2023), [35] Moufaddal et al. (2021), [39] Xu, Lu, & Zhan (2024)
Digital Twins and Simulation Architecture	[19] Zhang et al. (2023), [21] Hussein &Moharram (2023), [32] Werbińska-Wojciechowska et al. (2024), [22] Fernández-Caramés et al. (2019),
Cyber-Physical Systems and Interoperability	[18] Park et al. (2024), [36] Zhang (2018), [37] Oks et al. (2024), [38] Suárez-Riveros et al. (2021)
Sustainability and Urban	[23] Bartolini et al. (2019), [33] Edouard et al. (2022), [34] Tonelli et al. (2021)

Theme	Representative References
Logistics	
Security, Robustness, and Explainability in AI	[17] Zhao et al. (2021), [19] Zhang et al. (2023), [32] Werbińska-Wojciechowska et al. (2024)
Methodologies and Benchmarking Needs	[8] Roodbergen& Vis (2009), [31] Tubis&Rohman (2023), [9] Mostofi&Erfanian (2018)

Note: Numbers in brackets correspond to the reference list used in the article and respect its citation order.

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