Towards energy-aware operational decisions for automated guided vehicles: A review

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Automated Guided Vehicles (AGVs) are widely used for material handling across various industries, such as warehouses, manufacturing plants, and automated container terminals. As AGVs are battery-powered, it is necessary to schedule AGV's tasks considering energy-related aspects. That is, understanding how an AGV's energy is consumed or recharged in a given operational environment is crucial to optimizing both operational efficiency and energy consumption. This article presents a comprehensive analysis of energy-aware AGV operations, emphasizing three critical areas: the impact of the operational environment, energy consumption modeling, and energy-aware decision-making for scheduling and path planning. This article examines the layout structures and energy supply strategies in two different environments: automated container terminals and workshops, to understand the environmental impact on AGV energy efficiency. A comprehensive review of energy consumption models provides insight into the physical characteristics of AGVs' energy consumption. Finally, we provide variations of task scheduling and path planning problems that explicitly take into account such energy aspects and introduce how literature tackles to solve those problems.

Keywords: AGV Scheduling, automated guided vehicles (AGVs), battery management, energy consumption modeling, energy efficiency, optimization, path planning

1. INTRODUCTION

Automated Guided Vehicles (AGVs), first introduced in the 1950s, have become vital for material handling across various industries such as warehouses, manufacturing plants, and automated container terminals. Over the years, extensive research has been conducted to improve AGV technologies, particularly in the areas of navigation, path planning, and fleet management [1].

Since most AGVs are battery-powered, it has become more important to make operational decisions by considering how AGVs consume and recharge the energy as the deployment scale of AGVs significantly grows [2].

Recent studies have explored various techniques of AGV operational decisions integrated with energy management. For instance, Gallesi et al. [3] addressed AGV scheduling within the Pick and Delivery Problem (PDP) context, presenting a mathematical formulation that integrates battery-charging strategies under varying load types. Wu et al. [4] examined energy sources for energy consumption modeling and proposed charging technologies for Automated Mobile Robots (AMRs). Graba et al. [5] investigated an offline trajectory path planning algorithm to improve a robot's battery life.

While these studies offer valuable insights as to how AGVs' energy management is to be designed, it is necessary to provide a comprehensive review that systematically integrates the influence of operating environments, energy consumption models, and optimization strategies for AGV operations.

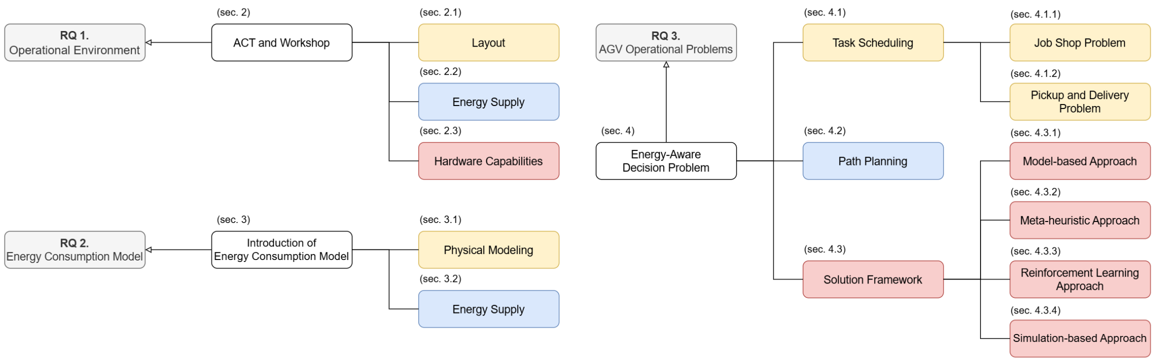


Figure 1 – Organization of this paper with 3 research questions: operational environment, energy consumption model, AGV operational problems

To address this gap, this survey provides a structured analysis of energy-efficient AGV operations by examining three key research questions, operating environment, energy consumption models, and AGV operation problems, each of which is addressed in a dedicated section. Fig. 1 provides a visual roadmap of how the paper is organized.

Firstly, the operational environment significantly affects the energy consumption patterns when an AGV performs diverse types of operations. The environment consists of multiple and intertwined factors including, but not limited to, the layout of work or charging stations that constrain the AGV's movement, the energy supply mechanism (e.g., battery charging or swapping), and the AGV's hardware capabilities (e.g., battery capacity or speed). We analyze those factors to understand how the interplay among many environmental factors affects the energy consumption of AGVs.

Secondly, we investigate how an AGV's energy consumption is accurately modeled to reflect its physical characteristics. In particular, energy consumption is influenced by several factors, such as the size of an AGV's payload and how far it is transported. Approaches to abstract such energy consumption vary depending on how many details of the physical characteristics are to be modeled and what data sources are available for modeling. We introduce two primary approaches for constructing these models: physics-based modeling and data-driven modeling.

Thirdly, we introduce how tasks should be assigned to a range of AGVs and how those AGVs move around according to the environment layouts. We categorize these problems into three types: Job Shop Problems (JSPs), Pickup and Delivery Problems (PDPs), and Path Planning Problems (PPs). We introduce how each problem is mathematically formulated in terms of optimization objectives and constraints; based on those base-type problems, further variations can be made to reflect the domain-specific environment. In addition, we introduce multiple categories of solution frameworks, including model-based, meta-heuristic, or reinforcement learning approaches and compare them in terms of scalability and computational efficiency.

2. OPERATIONAL ENVIRONMENT OF AGVS

The operational environment of AGVs, which comprises the layout, task characteristics, and hardware capabilities, significantly influences their energy consumption. Specifically, this paper examines the operation of AGVs in two specific environments: Automated Container Terminals (ACTs) and workshops, as illustrated in Fig 2.

ACT is typically used in outdoor port operations where containers should be loaded, unloaded, and transported from one place to another using automated crane systems. On the other hand, workshops are typically used in indoor environments to manufacture goods or components according to a specific sequence. Some aspects of the two environments commonly apply to the AGVs' operations, while some other aspects uniquely appear in one environment. For example, due to the differences in their scale and task-specific requirements, AGVs' behavior and energy consumption patterns are very different in those two environments.

In the ACT, AGVs work with **Quay Cranes (QCs)** and **Yard Cranes (YCs)** to transport the containers from vessels to storage areas. QCs unload containers from vessels and transfer them via designated paths through the buffer lane (auxiliary lane). The containers are then delivered to the YCs, which move them to the designated storage location. AGVs return to the QCs to maintain continuous transportation to pick up the next container. In the workshop, AGVs transport items between **depots** and **stations** (or **machines**). They retrieve items from the depot, deliver them to assigned workstations, and repeat the cycle.

2.1 Layout: ACT and workshop

In both environments, the layout structure is a critical factor influencing AGV performance. A layout should be designed to ensure that AGVs can navigate with minimal obstruction. This will enable them to complete tasks like transporting materials or performing pickup-and-delivery operations with reasonable speed and achieve the expected processing throughput.

The layout also significantly affects the energy consumption of AGVs. Specifically, the spatial arrangement of elements along the AGV path direction and the presence of spatial constraints, such as storage grids and restricted zones, affect AGV navigation differently, resulting in complex energy consumption patterns.

Table 1 compares different AGV warehouse layouts, highlighting the stations within each layout and the corresponding AGV path configurations.

Table 1 – Comparison of various layouts in an AGV Warehouse (A: Automated container terminal W: Workshop environment)

Ref	Layout Type	Stations/ Obstacles	Path Direction
[6]	(A) Ship Harbor	Battery Stations, Quey Cranes and Yard Cranes	Along Transport Grid
[8]	(A) Transport Grid	Quey Cranes and Yard Cranes	Omnidirectional
[9]	(W) Square Map with Obstacles	Rectangular Obstacles	Omnidirectional
[10]	(W) Shop Floor Layout	Charging Stations	Bidirectional
[11]	(W) Flexible Manufacturing Cell	Material Storage Areas	Bidirectional
[12]	(W) Product Line	Loading/Un-Loading, Buffer, Charging Stations	Bidirectional

A typical AGV movement can be either along a transport grid, bidirectional, or omnidirectional. An AGV moving on a transport grid follows predefined paths along a structured layout. In some cases, an AGV can move in a bidirectional motion, allowing it to travel forward or backward along the same path. On the other hand, AGVs can also move in an omnidirectional manner, enabling more flexible navigation in any direction.

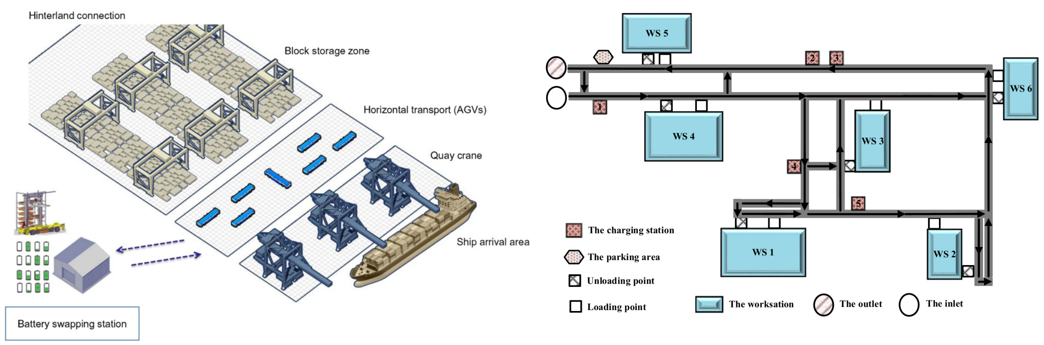
Spatial constraints, such as racks, obstacles, and storage grids, significantly influence AGV navigation and energy efficiency. Zhong et al. [13] addressed how spatial constraints in container terminals, including AGV-mate capacities and buffer zones, impact route selection, task assignment, and overall energy efficiency. Wang et al. [14] considered the presence of obstacles and depot placements to optimize AGVs' route sections. Duan et al. [15] emphasized the role of spatially-distributed cluster zones and dynamic task scheduling to avoid obstacles while ensuring the AGVs' operations are more energy-efficient.

Furthermore, Xiao et al. [16] illustrated the relation of the battery swapping/charging station position (outside/inside the operational area) and their influence on energy efficiency, further emphasizing the role of spatial layout in AGV operations. Tu et al. [17] showed efficient path planning for obstacle-moving environments, where the layout of the environment changes over time due to the moving obstacles. The presence of obstacles increases the computational complexity, making it essential for the path-planning algorithm to adjust and reconfigure to ensure energy efficiency.

2.2 Energy supply

It is crucial to consider how energy is supplied to AGVs as it affects operational efficiency. That is, an AGV's battery should be regularly replenished since the battery capacity is limited. Therefore, such constraint necessitates that AGVs temporarily leave their designated operational areas, disrupting workflow and overall operational efficiency. We introduce two primary methods to replenish an AGV's energy.

Battery charging: Some AGVs are equipped with batteries that cannot be easily detached, making swapping them with new ones difficult. Those AGVs must regularly



(a) Battery-swapping stations far from the operational area

(b) Battery-charging stations within the operational area

Figure 2 – Layouts of an Automated Container Terminal (ACT) with QCs and YCs [6] and a workshop with depots and stations [7]

visit charging stations and recharge them to continue their operations. During the charging stage, an AGV will be unavailable, and its duration is often significantly long, depending on the capacity and types of batteries.

Battery swapping: One can use a battery-swapping strategy for those AGVs equipped with detachable batteries; an AGV visits a swapping station, and operators can swap a discharged battery with a new one. The swapping period is typically much shorter than the charging time, so its effect on the operational time is relatively smaller compared to the battery-charging strategy. However, since the battery-swapping stations require a much larger infrastructure to stock many batteries, they are often located far from the workspace. In addition, traffic congestions entering or exiting from the swapping stations may occur when many AGVs are deployed [18]. Those factors affect the travel time between the workspace and the swapping stations, negatively affecting operational efficiency.

Fig. 2a and Fig. 2b illustrate the spatial arrangement of the battery-swapping stations (terminal bottom left) in the ACT and battery-charging station (rectangle with red dots) in the workshop environment. The battery-charging stations are placed within or near the operational areas, allowing frequent charging. In contrast, battery-swapping stations are typically fewer in number and located farther from the operational areas.

Some works such as [6], [18], [19–22] exclusively consider the battery-swapping method as their energy replenishment strategy in the container terminal setting. On the other hand, some work employs the battery-charging method, such as [10], [23–27]. The battery-charging method is used in both container terminal settings and workshop operations.

2.3 AGV hardware capabilities

A transport task should be assigned to an AGV considering its hardware specifications since they influence the energy consumption of AGV operations, such as battery capacity and an AGV's speed.

The studies from [19, 28] explicitly incorporate battery capacity as a key factor, modeling scenarios where AGVs must periodically recharge or optimize energy consumption. Zhou W. F. et al. [19] integrated energy-aware scheduling with battery-swapping tasks, proposing a double-limit battery-swapping approach in which battery replacement occurs when the AGV battery level falls between 10% and 30%. In contrast, Zhou, S. et al. [28] focused on AGV scheduling with battery charging, considering a single-threshold strategy where charging is triggered when the battery level drops below a predefined threshold.

The AGV's speed is another factor influencing both the makespan of transportation tasks and energy consumption, and there is a trade-off between the two. A higher speed reduces transportation time, accelerating the overall manufacturing workflow. However, this increases the energy consumption of AGVs [29] and a collision probability between the AGVs; this necessitates additional collision detection and mitigation mechanisms [30]. Conversely, reducing AGV speed helps conserve energy [31], sacrificing transportation time and potentially increasing the overall makespan. If the AGV speed is excessively slow, the total energy consumption may rise due to prolonged operations to complete all tasks [32].

3. ENERGY CONSUMPTION MODEL

Energy consumption should be reasonably modeled to make better decisions in AGV operations, such as task assignments or path planning. However, many studies remove the details of the energy consumption model; for example, much work assumes AGVs spend constant energy, neglecting their operation types or load conditions.

Some recent research aims to explicitly model such energy consumption incorporating various components, such as the total weight [24, 33], the travel distance [34], energy sources (e.g., batteries) [35, 36], and fuel consumption [37]. In addition, robots' kinematic elements such as speeds[38, 39], friction[40], and gravity[41], are important factors to consider for accurate energy consumption modeling.

3.1 Physics-based modeling

Approaches to constructing energy consumption models can be categorized into physics-based modeling and data-driven modeling. Physics-based modeling creates energy models using the fundamental laws of physics. Alternatively, energy models can be derived from the kinematic characteristics of mobile robots, incorporating parameters such as linear and angular velocities [41, 42]. Some approaches considered energy sources like batteries [35, 42] or motor models [35, 41, 42].

Another method is to design scenario-specific AGV energy models based on an AGVs' operations [2, 38, 43–45]. For example, [2, 44] developed energy consumption models that consider different AGV states, including accelerated motion, uniform motion, and standby mode. Tian et al. [38] proposed the energy consumption model accounting for both the energy consumed during task execution and the start-up energy required to initiate tasks. Xin et al. [43] introduced an energy consumption model specific to AGV operations in ACT, distinguishing between inbound operations (from yard cranes to

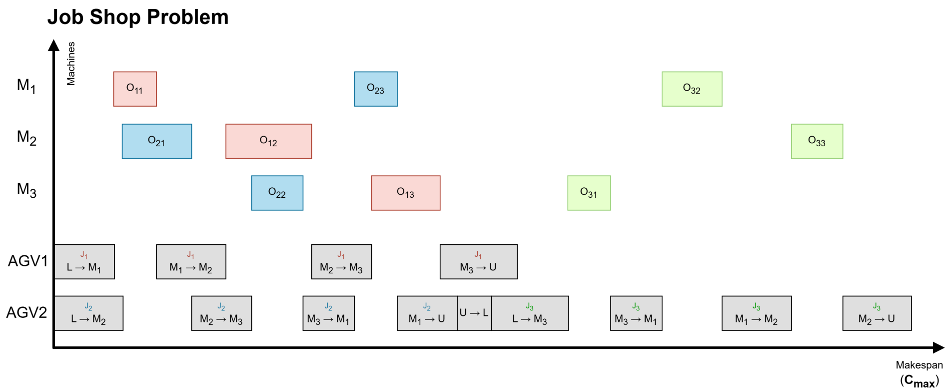


Figure 3 – Job Shop Problem (JSP): Gantt chart

quay cranes) and outbound operations (from quay cranes to external stacking areas). Additionally, Zhang et al. [45] designed an AGV energy model that differentiates between loaded and unloaded conditions.

Some approaches concentrated on the interactions between several physical elements to construct an energy model instead of focusing on individual elements. For example, [34, 46] modeled the energy consumption by multiplying the travel distance and weight, while others characterized relationships between physical elements used in the energy model [45, 47]. Such a modeling technique may not precisely capture the details of individual physical elements, but it can model the emergent characteristics occurring when those elements interact with each other.

3.2 Data-driven modeling

Data-driven modeling constructs energy consumption models based on experimental energy consumption data. One method is to create a generic energy model and refine it by fitting the parameters, such as speed, load, and route inclination, based on experimental results collected under various operational conditions [48]. Another approach uses linear regression on experiment data in which energy consumption changes according to the robot weights [24]. Some approaches propose the probabilistic battery model that accounts for the current battery states and the state transitions influenced by the charging and discharging process [36]. In the work of Naumov et al. [49], the Verein Deutscher Ingenieure (VDI) benchmark is used to evaluate the energy models. Data-driven approaches can achieve more accurate energy consumption models for a specific robot or environment than general physics-based modeling. However, they require extensive experiments and data to develop accurate models and are challenging to apply to different environments once a model has been constructed.

4. ENERGY-AWARE DECISION

The primary goal of an AGV is to transport materials between the designated start and end point efficiently. In systems involving multiple mobile robots, operational strategies must address critical decisions, including task scheduling and path planning, to optimize resource utilization and overall system performance such as the makespan, total task completion time, and the total distance of the all AGVs.

Task scheduling is the process of assigning a set of transport tasks to the mobile robots, with each task containing a specific start and end location at the certain time or in the specific sequence. Path planning, on the other hand, focuses on determining conflict-free routes, AGVs do not occupy the same location simultaneously, for each AGV once tasks have been assigned.

While makespan, the total task completion time, has traditionally been the primary performance metric, it is now increasingly important to consider energy consumption as an additional factor. Considering the energy not only reduces operational costs but also aligns with sustainability goals by minimizing environmental impact [40, 51]. Integrating energy-aware strategies into operational decisions not only reduces operational costs but also supports sustainability goals by minimizing environmental impact.

One primary goal of AGV is to transport materials among different locations efficiently. The operational strategies to achieve the goal can be broadly categorized into task scheduling and path planning; each needs to optimize various objectives, such as resource utilization, makespan, task completion time, and travel distances of AGVs.

Task Scheduling decides how to assign a set of transport tasks to the mobile robots, considering requirements such as transport locations, sequences, or the time of arrival. Path planning, on the other hand, decides the routes of mobile robots to achieve the goal meeting spatial

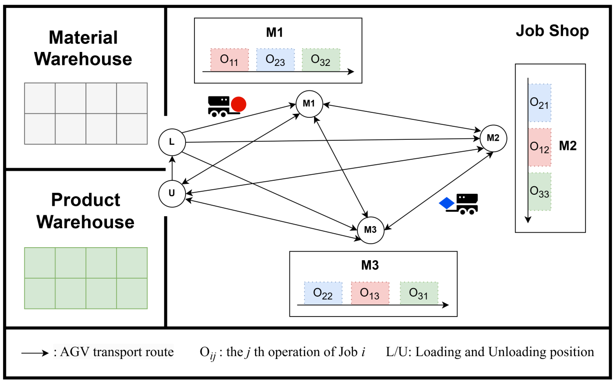


Figure 4 – JSP: Environment [50]

Table 2 – JSP: Operation processing times on each machine

t	M_1	M_2	M_3
O_{11}	5	-	-
O_{12}	-	10	-
O_{13}	-	-	8
O_{21}	-	8	-
O_{22}	-	-	6
O_{23}	5	-	-
O_{31}	-	-	5
O_{32}	7	-	-
O_{33}	-	6	-

Table 3 – JSP: Travel time for each location

t	L	U	M_1	M_2	M_3
L	-	4	7	8	9
U	4	-	7	8	9
M_1	7	7	-	8	6
M_2	8	8	8	-	7
M_3	9	9	6	7	-

constraints such as finding a conflict-free route —AGVs do not occupy the same location simultaneously —for each AGV once tasks have been assigned.

While traditional performance metrics, such as makespan or task completion time, mostly focused on how well or efficiently one completes the assigned tasks, considering energy consumption has become increasingly important. Such energy consideration reduces operational costs and aligns with sustainability goals by minimizing environmental impact [40, 51].

4.1 Task scheduling

The AGV task scheduling problem can be categorized into the **Job Shop Problem (JSP)** and **Pick and Delivery Problem (PDP)** based on the characteristics of operations performed at machines or stations.

4.1.1 Job shop problem

The Job Shop Problem (JSP) is a scheduling problem involving the sequential processing of operations composed of a set of jobs. Also, it requires determining which AGV should perform the transport tasks for each job in a certain time or sequence.

The JSP is illustrated in figures 3, 4 and tables 2 and 3. Suppose a set of jobs $J = \{J_1, J_2, ..., J_n\}$, a set of machines $M = \{M_1, M_2, ..., M_m\}$, and a set of AGVs $R = \{R_1, R_2, ..., R_k\}$ are given.

In every transport job, AGVs start from the loading point where raw materials are available. The AGVs travel from one machine to the other according to the job's processing sequence and then take the finished product to an unloading point to store it in the product warehouse.

The problem is characterized by the following constraints:

- **Operational sequence**: Each job J_i is composed of a sequence of operations $\{O_{i1}, O_{i2}, ..., O_{ij}\}$. For example, in order to complete job J_1, operations O_{11}, O_{12}, and O_{13} (all represented as red) must be processed sequentially on machines M_1, M_2, and M_3, respectively.
- **Processing time**: Each operation O_{ij} is processed for a specified duration t_{ij}. Table 2 presents the processing times for each operation on different machines. For instance, operation O_{11} requires 5-time units to be completed on machine M_1.
- **Travel time**: The travel time between different locations is assumed to be known. Table 3 shows a two-dimensional matrix showing travel times between various locations. For example, the AGV route from L (loading point) to M_1 (Machine 1) takes 7-time units, then from M_1 to M_2 (Machine 2) takes 8-time units, and finally from M_2 to U (unloading point) takes 8-time units.
- **Machine and AGV availability**: A machine can only process one operation at a given time. Similarly, AGVs can handle only one transport task at a time.

The objective of the JSP is to optimize performance metrics, such as minimizing makespan, total time required to complete all jobs, and total tardiness, total delay of the jobs from their deadlines.

The Flexible Job Shop Problem (FJSP) extends classical JSP by allowing operations to be processed on multiple machines. FJSP is widely applied in modern manufacturing environments, where systems need to flexibly process diverse production demands such as engine cooling fan manufacturing or casting production. Table 4 shows that certain operations (*e.g.*, O_{21}) can be executed on different machines (*e.g.*, M_1, M_2) whose processing times vary. If one machine is occupied with another operation, AGVs have an another option to use the alternative machine.

The Dynamic Job Shop Problem (DJSP) addresses scheduling in environments where uncertain operational disruptions occur, such as machine breakdowns or urgent task arrivals. Fig. 5 illustrates an example of an AGV break-

Table 4 – FJSP: Operation processing times on each machine

t	M_1	M_2	M_3
O_{11}	5	-	-
O_{12}	-	10	-
O_{13}	-	-	8
O_{21}	6	8	-
O_{22}	7	-	6
O_{23}	5	-	1

down scenario. Initially, AGV 1 was assigned to the transportation task for Job 1 (Red), while AGV 2 was handling the transportation task for Job 2 (Blue). However, due to the unexpected failure of AGV 1, it could not complete its transportation tasks. As a result, AGV 2 takes over the transportation tasks for Job 1 ($J_1 : M_2 \rightarrow M_3$) to ensure continuity in operations despite the disruptions.

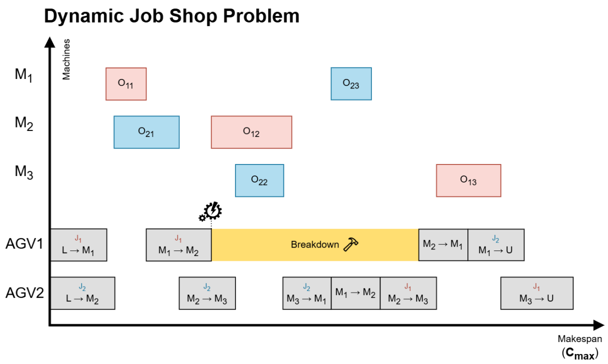


Figure 5 – Dynamic Job Shop Problem, In Job J_1, operation O_{11} rRed, processed in Machine M_1) requires an AGV transport task from L_1 to M_1, represented as $J_1 : L_1 \rightarrow M_1$

4.1.2 Pickup and delivery problem

The Pickup and Delivery Problem (PDP) is a scheduling problem to transport the items between designated pairs of locations, typically from a pickup point to a corresponding delivery destination. Fig. 6 shows the routes assigned to the AGVs and Fig. 7 illustrates the time taken to complete each transportation task. More specifically, the set of mobile robot R is responsible for transporting task i ($i = 1, 2, ..., n$) from the set of pickup locations $P = \{P_1, P_2, ..., P_n\}$ to the corresponding delivery destinations $D = \{D_1, D_2, ..., D_n\}$. Each task i consists of multiple phases, picking up an item from its designated pickup location P_i and delivering to its destination D_i.

Unlike the JSP, where the specific items must be processed in particular machines or stations and delivered in a predefined sequence, the transportation tasks in PDP do not require following a particular sequence. In particular, the following assumptions are made:

- There are no collisions or traffic congestion among AGVs.
- The delivery times between locations and the transport times from P_i to D_i, are known in advance.

The objective is to determine which mobile robot should be assigned to each task to minimize a given optimization criterion, such as the makespan.

Several variations of PDP research incorporate energy-aware scheduling from two perspectives: (1) Pickup and delivery with battery replenishment strategies and (2) pickup and delivery with multi-load handling.

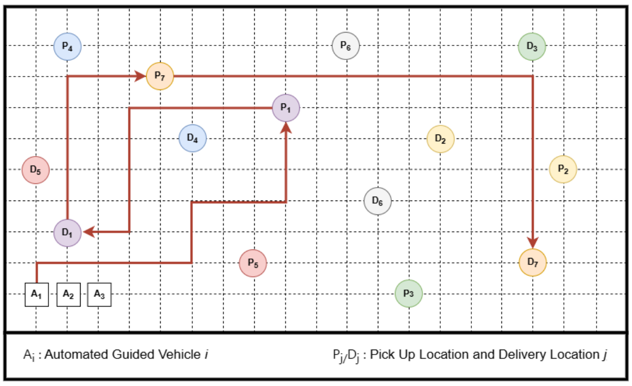


Figure 6 – Pickup and delivery problem: Environment

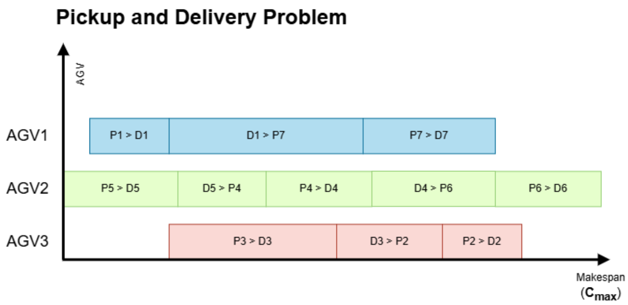


Figure 7 – Pickup and delivery problem: Gantt chart

Pickup and delivery with battery replenishment strategies

Most studies assume that mobile robots operate with sufficient battery power to complete transportation tasks throughout their operating time. However, mobile robots must recharge in practical applications when their battery levels become critically low.

Recharging strategies for mobile robots generally fall into three categories: full recharging, partial recharging, and battery swapping.

- **Full recharging**: This approach involves fully charging the battery before resuming operations. Since complete charging takes significant time, the number of available (idle) AGVs for transportation decreases as a higher priority is given to battery charging over task execution.
- **Partial recharging**: AGVs are partially recharged only up to a certain threshold (e.g., 70 %) rather than waiting for a full charge. This method can reduce downtime and optimize operational costs compared to full

recharge, as not all mobile robots need to be used at all times. However, frequent partial charging may require AGVs to visit charging stations more often, potentially affecting operational efficiency.

- **Battery swapping**: This method involves replacing a depleted battery with a fully charged one at a battery station. While this reduces charging downtime, strategic battery management is needed to maintain a sufficient battery supply. Otherwise, a battery shortage might occur if multiple AGVs require battery replacement simultaneously.

Pickup and delivery with multi-load handling The Pickup and delivery problem with multi-load handling can be classified into two scenarios based on the payload types of AGVs: single-load and multi-load. As discussed in Section 3.2, both an AGV's weight and its payload impact an AGV's energy consumption.

In the single-load scenario, the AGV can be either loaded or unloaded. Once the AGV picks up an item from the pickup location, it must be transported to the delivery destination before collecting another item from a different pickup location. This scenario is common in ACTs, where Automated Guided Vehicles (AGVs) are restricted to carrying a single container due to their large size.

On the other hand, a multi-load scenario allows AGVs to pick up multiple items from different pickup locations without having to deliver each item immediately to its destination. This increases operational flexibility and energy efficiency by enabling multiple pickups in a single trip. However, one needs to make sure the AGVs do not load multiple items exceeding their maximum payload capacity limit.

4.2 Path planning

Path planning determines the route for each AGV from a start to a destination location while optimizing objectives, such as minimizing travel distance and reducing energy consumption. Each route consists of the sequence of locations or grid points that an AGV visits. In addition, it must satisfy constraints different from task scheduling, such as avoiding obstacles and ensuring timely arrival at the destination. Since the AGVs cannot occupy the location where the obstacles are present, their movement is highly dependent on the placement patterns of the obstacles. The environments of the path planning problem can be classified into static and dynamic environments.

In a **static environment**, all objects, such as stations and obstacles, remain stationary over time. The spatial aspects of the entire environment are assumed to be known in advance and it does not change over time. Due to this characteristic, the routes of AGVs can be predetermined, and operations can be scheduled accordingly without needing to change their routes.

Conversely, in a **dynamic environment**, AGVs encounter varying operational conditions that change over time, such as moving obstacles and machine breakdowns. In this condition, the AGV has to change its route in real time to adapt to the changing environmental conditions (e.g., change its route to avoid collisions). Efficient path planning under these dynamic environments is crucial to reduce unnecessary AGV stops and minimizing energy consumption.

4.3 Solution framework

This section presents the solution frameworks used for energy-aware decision problems: Job Shop Problem (JSP, section 4.1.1), Pickup and Delivery Problem (PDP, section 4.1.2), and Path Planning Problem (PP, section 4.2).

Table 5 categorizes existing studies based on problem types, their variations, and the methodologies applied. The problems are classified into three main categories: JSP (Classic JSP, Flexible JSP, and Dynamic JSP), PDP (Classic PDP, PDP with battery considerations, and PDP with load considerations), and PP (static and dynamic environments). The methodologies used to address these problems include the model-based approach, meta-heuristic approach, reinforcement learning approach, and simulation-based approach, which will be introduced in this section. Both model-based and meta-heuristic approaches are widely applied to all three problems. However, other approaches are applied to narrower problem categories; the reinforcement learning approach is used in JSP only, and the simulation-based approach is adopted for both JSP and PP.

4.3.1 Model-based approach

The model-based approach aims to find optimal solutions from mathematically defined models via existing solvers or suboptimal solutions through heuristic algorithms that encode a set of rules to make algorithmic decisions.

Mathematically-defined framework such as Mixed-Integer Linear Programming (MILP), dynamic programming, and decomposition strategies, offer the advantage of guaranteeing optimality for small-scale problems. However, their computational complexity grows exponentially, making them impractical for large-scale scenarios.

Homayouni et al. [52] presented a bi-objective MILP model that optimizes the scheduling of both machines and AGVs while incorporating speed-scalable resources. This model dynamically determines the processing speed

Table 5 – Comparison of the solution framework used for energy-aware decision problems: JSP (Job Shop Problem), PDP (Pickup and Delivery Problem), and PP(Path-planning Problem)

	JSP			PDP			PP	
Framework	Classic	Flexible	Dynamic	Classic	Battery	Load	Static	Dynamic
Model-based	[52]	[53–55]	-	[56–60]	-	-	[40, 59–69]	[70, 71]
Meta-heuristic	[72]	[50, 73–75]	-	-	[19, 28]	[2, 24, 43, 76]	[77–79]	[17, 77, 80, 81]
RL-based	-	[82–84]	-	-	-	-	-	-
Simulation-based	-	-	[85, 86]	-	-	-	[87]	-

of machines and the travel speed of AGVs. Jointly optimizing machine and vehicle scheduling enhances the interaction between machines and AGVs. Since speed selection is included in the decision variables, the model achieves energy efficiency without compromising productivity.

Xin et al. [57] introduced a rescheduling method that utilizes the current state measurements of AGVs to dynamically update the processing time of ongoing operations. The container handling process is modeled as a three-stage system, and the operations of AGVs are formulated as a discrete-event system with predefined constraints. The supervisory controller continuously monitors the current state of each AGV, including its position and velocity. Based on these state measurements, the controller updates the estimated processing time for remaining tasks and determines an optimized schedule by solving an MILP problem.

Heuristic approaches offer a practical alternative for complex problems by providing near-optimal solutions that can be more efficiently computed compared to obtaining theoretically proven optimal solutions. Such scalability becomes their key strength since it is relatively easy to incorporate more complex energy-efficient scheduling, which is increasingly important in industrial applications. In particular, rule-based systems can dynamically modify scheduling strategies based on fluctuating energy costs and unexpected operational changes [53][54].

However, these methods also have certain limitations. Since they heavily depend on problem-specific knowledge, their applicability to new or significantly different environments may be restricted. Additionally, in rapidly changing conditions, their effectiveness can decline unless further optimization techniques or real-time data-driven adjustments are integrated [55][56][53].

Xing et al. [58] reformulated the problem with the known delivery/handling sequences as a network by viewing AGVs and cranes as machines, then improves the network using a three-phase algorithm. Firstly, the algorithm finds a primal solution using an anticipation-based greedy algorithm. Then, the solution is optimized by adjusting the sequences of AGVs and cranes with branch-and-bound. Finally, the speed on non-critical paths is adjusted by modeling the relationship between speed and energy consumption as a mathematical function.

Xin et al. [61] presented a two-level energy-aware trajectory planning approach, formulated as an MILP problem, which is proposed for AGVs in automated container terminals. This method minimizes energy consumption while ensuring collision-free trajectories but has only been tested on small-scale systems with limited AGVs.

Henkel et al. [70] provided the energy dynamic window approach, which is applied to omnidirectional battery-powered mobile robots in dynamic environments. It reduces energy usage while maintaining the duration of time needed to reach the designated goal location. However, it does not account for energy losses like motor magnetization and resistance.

Constraint Programming (CP) and Satisfiability Modulo Theories (SMTs) solvers have been proposed to improve AGV scheduling and routing by ensuring conflict-free paths. These methods enhance computational efficiency and can solve large-scale industrial scheduling instances. Riazi et al. [59] proposed CP and SMT solvers combined with Benders decomposition which are employed to optimize AGV routing. However, scalability remains a concern in highly constrained environments such as intersections or battery-charging stations.

Priority-based speed control strategies have been explored to minimize AGV driving distances while avoiding conflicts, congestion, and waiting times. These approaches integrate search-based algorithms to improve operational efficiency. Zhong et al. [62] present a priority-based speed control strategy combined with a Dijkstra Depth-First Search (DFS) algorithm for AGV path planning in automated container terminals. This method reduces the number of conflicts, enhancing system performance but it does not consider AGV breakdowns or deadlock situations.

Classical shortest path methods like Dijkstra's and A* offer deterministic solutions but often lack adaptability in dynamic environments. Qing et al. [64], applied an improved Dijkstra algorithm to AGV path planning in Automated Storage and Retrieval Systems (AS/RS). They propose the methods that optimize travel time and energy consumption by reducing the number of turns. Frequent turns require the robot to decelerate and accelerate, making it challenging to maintain a high speed, increasing energy consumption. While effective in static environments, it does not handle dynamic obstacles or real-time changes, restricting its applicability.

Multi-objective AGV scheduling using a MapReduce framework has been proposed to optimize scheduling efficiency while minimizing total driving distance and waiting times. Shi et al. [60] presented a speed control strategy integrated with A* search algorithm-based shortest path planning within the MapReduce framework to improve execution efficiency. However, this model primarily focuses on static path planning and may struggle with dynamic obstacles, with its computational efficiency depending on hardware scalability.

4.3.2 Meta-heuristic approach

Meta-heuristics are general search techniques for solving optimization problems, mainly when the search space is significantly large. Instead of guaranteeing an exact optimal solution, they aim to efficiently find a good approximation through global exploration. Since they are not problem-specific, meta-heuristics are a flexible framework that can be applied to many optimization problems. Also, meta-heuristic scheduling algorithms have been widely studied for their effectiveness in outperforming traditional heuristic methods, particularly in solving NP-hard problems [73] , [88]. However, they face three key challenges: long execution times due to iterative processes, non-deterministic behavior from randomness, and susceptibility to local minima [88].

Genetic Algorithms (GAs) provide flexibility in optimizing multiple criteria but often require many generations to converge. Tu et al. [17] applied GAs to AGV path planning but there are struggles with dynamic obstacle handling, which limits the real-time effectiveness. Similarly, graph-based modifications like Basic Theta*, Phi*, and Jump Point Search improve path optimization but assume a functional SLAM system, assuming the robot already has a precise map for the whole environment. This limits their applicability in dynamic environments [63].

He et al. [50] designed a multi-objective evolutionary algorithm to integrate job-shop scheduling with AGV transport scheduling. A chromosome is encoded with four components: operation sequence, machine speed, AGV assignment, and AGV speed. The algorithm generates diverse solutions by incorporating three crossover operations: order crossover, partial-mapped crossover, and a customized crossover operator for AGV scheduling. The two-point mutation is then applied to modify solutions, and opposition-based learning is utilized to expand the search space and accelerate the algorithm's convergence.

Liu et al. [74] decomposed the FJSP-AGVs problem into four interrelated sub-problems: operation sequencing, machine selection, speed selection, and AGV assignment. They proposed a cooperative coevolutionary algorithm to optimize sub-problems simultaneously, assigning each to a separate population. A multi-rule-based heuristic is employed, enhancing the diversity of initial solutions. The algorithm incorporates two cooperative evolution strategies based on critical paths, the longest sequence of operations from the first to the final operation in the workflow. Precedence operation crossover and insertion operations are applied to the operation sequencing population, while uniform crossover and critical path-based mutation are applied to the machine selection population. Furthermore, the cooperative coevolution mechanism ensures that the four populations evolve independently while exchanging information and collaborating throughout the optimization process.

Xu et al. [75] proposed an efficient heuristic algorithm based on NSGA-II. Unlike NSGA-II, the algorithm incorporates a two-layer encoding method that separately represents operation sequences and machine assignments while dynamically selecting AGVs to optimize transport efficiency. They also employ a greedy insertion decoding strategy to minimize idle machine time and ensure optimal job placement. Additionally, customized crossover and mutation operators and a critical path-based local search enhance solution diversity and convergence speed.

Zhou et al. [19] developed a discrete multi-objective Whale Optimization Algorithm (WOA), which extends WOA to co-optimize AGV operations considering battery swapping. The proposed model initializes the initial population using a load-balancing-based method, which distributes tasks more evenly among AGVs by considering the average driving distance per AGV. The task sequence and battery-swapping schedule are jointly optimized, dynamically adjusting to battery levels. The algorithm employs reversal operation, multiple crossover strategies, and opposition-based learning to generate and refine new solutions.

Abderrahim et al. [72] developed a variable neighborhood search-based algorithm to optimize AGV scheduling with integrated battery constraints. The algorithm employs dynamic neighborhood adjustments, including task swaps, AGV route reordering, and machine assignment changes, to iteratively refine solutions through variable neighborhood descent. Battery management is incorporated by routing AGVs to the nearest charging stations when their battery levels drop below a critical threshold. Charging times are dynamically included in task sequences.

Zhou et al. [28] utilized a large neighborhood search algorithm for AGV scheduling in container terminals, focusing on battery and spatial constraints. Neighborhood operators explore task removal and reinsertion strategies. Precomputed distances between quay cranes, yard locations, and charging stations are embedded into the model, enabling precise AGV route adjustments.

Xin et al. [43] introduced an improved adaptive genetic algorithm aimed at minimizing the total energy consumption of AGVs in Automated Container Terminals (ACTs). Instead of categorizing AGV energy consumption based on vehicle state and load, the authors propose a model that accounts for the operational characteristics of AGVs. Specifically, they develop distinct energy consumption models for inbound and outbound operations to capture differences in destination points better.

In inbound operations, AGVs transport containers between Quay Cranes (QCs) and Yard Cranes (YCs), each with a unique, predetermined destination. In contrast, outbound operations involve AGVs moving containers from the stack point in the YCs to multiple possible destinations near the designated QCs. Unlike the methods that focus on the vehicle state and load, this approach can capture the task state from the terminal equipment, including YCs and QCs, allowing cooperative task scheduling between AGVs and QCs.

The studies conducted by [76] and [24] explored scenarios within warehouse environments where AGVs are capable of visiting multiple stations provided that the load does not exceed their capacity. These studies employ hybrid Adaptive Large Neighborhood Search (ALNS) and Non-dominated Sorting Genetic Algorithm III (NSGA-III) to optimize AGV operations, aiming to minimize total energy consumption by effectively managing both scheduling and routing under multi-load conditions.

Wang et al. [89] presented a bi-level optimization approach designed to minimize the overall energy consumption in ACTs. The energy consumption model consists of energy consumption in different states, including the idle, uniform speed with no-load/full-load, and acceleration with no-load/full-load. The proposed solution framework consists of upper-level and low-level models. The upper-level model aims to minimize the total energy consumption of all AGVs, whereas the lower-level model focuses on minimizing the energy consumption of a single AGV.

Energy-efficient path planning for single-load AGVs has also been investigated in manufacturing workshops. These approaches aim to minimize transport distance and energy consumption. Zhange Z. et al. [2] propose an Energy-efficient AGV Path Planning (EAPP) model, utilizing a two-stage solution method that finds the shortest route and selects the one with minimum energy consumption. A Particle Swarm Optimization (PSO)-based method is also used for multi-objective global optimization. However, the study focuses only on single-load AGVs, limiting its applicability to multi-AGV systems.

4.3.3 Reinforcement learning approach

The Reinforcement Learning (RL) approach formulates the task scheduling problem as a sequential decision-making problem, expressing the relation between the environmental state, agent, and action. By evaluating actions at each step, agents iteratively learn optimal policies to improve task scheduling efficiency. This method is particularly effective for handling real-time disruptions such as machine breakdowns and new job arrivals.

Bar et al. [84] proposed an online scheduling method using multi-agent DQN. While agents make scheduling decisions and learn independently, they share a common Q-value function to stabilize training and improve efficiency. Their experiences are stored in a collective replay memory, enhancing generalization across different scheduling scenarios. This approach allows the system to dynamically adjust schedules and efficiently allocate tasks in highly variable environments.

Li et al. [82] modeled dynamic flexible JSP with limited AGV resources as a Markov decision process, where the agent is a reinforcement learning model. The agent interacts with the shop floor environment and is implemented using a hybrid DQN. This network extends DQN by incorporating double Q-learning, prioritized replay, and a soft target network update policy. These enable the agent to perceive disturbance events and adjust its scheduling strategy accordingly.

Zhang F. Y. et al. [83] proposed a Deep Reinforcement Learning-based Memetic Algorithm (DQNMA) to integrate energy considerations into flexible job shop scheduling within multi-AGV systems. This method aims to minimize both makespan and total energy consumption but struggles with formulating explicit energy-saving strategies, limiting practical implementation.

4.3.4 Simulation-based approach

The simulation-based approach provides robustness by capturing the dynamic behavior of the environment and AGV while accounting for uncertainty. Compared to the other methods, such as traditional mathematical models, they often simplify real-world dynamics, making it challenging to develop energy-efficient strategies in practical settings.

Benhafssa et al. [85] utilized a multi-agent simulation as a decision-making tool to address the dynamic FJSP. They captured the energy consumption of both AGVs and workstations, considering AGV energy usage in loading, unloading, and standby states. Additionally, the simulation is conducted under various production scenarios, incorporating different processing times for operations, AGV fleet sizes, and production types.

Tang et al. [86] established a simulation model for QCs and AGV operations using agent-based and discrete event simulation modeling. The model accounts for stochastic order arrivals, the movement of the QCs, and interactions with AGVs and External Trucks (ETs). Energy consumption of QCs, AGVs, and ETs is quantitatively estimated every discrete time.

Energy-efficient path-following control systems have been developed to minimize the tracking error between the actual and desired trajectory of AGVs while optimizing energy consumption. Holovatenko et al. [87] proposed an optimal control system based on a state-space model and a Riccati equation is proposed to determine an energy-efficient control law. This method improves battery efficiency and extends the AGV's driving range but is primarily designed for two-wheel AGVs, limiting generalization to other AGV configurations.

5. DISCUSSIONS

5.1 Distinctions in AGV energy research

In this article, we explore energy-aware decision-making problems and energy modeling for AGVs. In the context of energy-aware decision-making, AGVs differ in their operating environment from other battery-powered systems like drones and Electrical Vehicles (EVs). While drones and EVs navigate open environments with defined starting and ending points and flexible routes, an AGVs operate in structured settings with routes guided by a predefined grid layout. In energy modeling, an AGV energy consumption model is primarily influenced by payloads and travel distances. In contrast, energy modeling for drones incorporates aerodynamic factors, such as wind speed and direction, which affect energy consumption due to air resistance [90, 91]. Similarly, EV energy modeling is influenced by road conditions, such as terrain slope variations and traffic congestion. Steeper slopes demand greater power for EVs to ascend, accelerating battery depletion [92, 93]. Traffic congestion causes frequent stops and starts, lowering efficiency and increasing energy use due to repeated acceleration [94].

5.2 Future directions

One underexplored area in AGV energy research is the handling of uncertainty in dynamic operational environments, particularly within task scheduling for energy-aware decision-making. Existing scheduling approaches often simplify the problem by assuming AGVs maintain constant speeds, neglecting the impact of acceleration and deceleration motions to reduce computational complexity. Yet, as discussed in section 3, speed significantly affects AGV energy consumption modeling. Although [95] incorporates dynamic AGV speeds into scheduling, its scope is limited to coordination between YCs and AGVs, leaving integration with QCs unaddressed. Furthermore, dynamic events in scheduling remain poorly handled; in scheduling problems such as JSP and PDP, jobs and tasks are typically predefined and known in advance [56, 96]. However, real-world scenarios often involve online orders, those received dynamically during operations, that introduce uncertainty, requiring adaptive scheduling to accommodate the issues.

Another critical gap lies in the integration of path planning and scheduling with charging considerations. Current research has tackled these challenges in two separate forms: optimizing path planning with charging needs and scheduling tasks while accounting for AGV battery constraints. However, a unified approach combining path planning and scheduling, while jointly addressing charging requirements, remains largely unexplored.

To address these shortcomings, future studies should investigate coordinated scheduling strategies that encompass QCs, YCs, and AGVs simultaneously, or shift focus to workshop environments by incorporating variable speeds and acceleration dynamics into the problem formulation. Developing adaptive frameworks that account for real-time uncertainties, speed variations, and charging integration will be essential for creating robust, energy-efficient scheduling solutions tailored to practical AGV deployments.

6. CONCLUSION

This article explored key aspects of energy-efficient AGV operations, addressing research questions and analyzing various factors influencing AGV energy performance.

First, we examined the operating environment's impact on AGV energy consumption. We focused on two primary operational environments, automated container terminals and workshop environments, analyzing key factors such as layout structure and energy supply methods. Additionally, we reviewed AGV hardware capabilities, including battery capacity and speed, which directly affect energy efficiency. Furthermore, we investigated battery replenishment strategies, comparing charging and swapping methods and their implications for AGV operations.

Second, we examined different approaches to modeling AGV energy consumption. Two primary methodologies were considered: physics-based modeling, which applies fundamental physical laws to define energy consumption, and data-driven modeling, which relies on real-world historical data.

Finally, we discussed the systematic formalization of energy-aware AGV operational problems, particularly in scheduling and path planning. We categorized these problems into job shop scheduling, pickup and delivery, and path planning, analyzing their mathematical formulations, including commonly used objective functions and constraints. We also examined solution approaches for each problem, evaluating their scalability and computational efficiency in AGV operations.

The survey provides a comprehensive perspective on research related to energy-aware AGV operations. By leveraging insights from diverse operational environments, energy modeling strategies, and optimization techniques. Compared to other battery-powered systems like drones and EVs, energy modeling and energy-aware decision-making for AGVs are simplified by their structured environments and the main influence of payloads and travel distances on energy consumption, enabling easier modeling of real-world problems. Future work may focus on addressing key gaps, such as managing uncertainty in dynamic scheduling, incorporating variable speeds and acceleration dynamics, and integrating path planning and task scheduling to develop energy-efficient solutions for real-world AGV deployments.

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