Job Shop Scheduling with AGV Charging Considering Travel Time and Processing Time

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INFORMATION

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ABSTRACT

Job Shop Scheduling Problem with Automated Guided Vehicles (JSP-AGV) better aligns with the real-world workshop scenarios and has become a research hotspot. However, optimizing JSP-AGV with AGV charging remains a significant challenge. The comprehensive JSP-AGV model incorporated AGV charging is established, where charging is mandatory and interrupts the transportation task. Then, an improved genetic algorithm with a hybrid initialization strategy and problem-specific crossover and mutation operators is devised to minimize the Exit Time (ET). Extensive simulations are conducted to evaluate the model and algorithm. Furthermore, Design of Experiments (DoE) is employed to quantitatively analyze the impact of three critical system parameters, such as AGV battery capacity, AGV quantity, and travel time-to-processing time ratio. The analysis reveals that the travel time to processing time ratio determines the scheduling bottlenecks in JSP-AGV. Orthogonal experimental results indicate that for time-related metrics, including ET, machines waiting time for jobs, jobs waiting time for machines, AGVs waiting time for jobs, jobs waiting time for AGVs, the influencing factors are ranked in descending order of importance as follows: travel time to processing time ratio, AGV quantity and AGV battery capacity. In contrast, for AGV charging frequency metric, the order of the influence is AGV battery capacity, travel time to processing time ratio and AGV quantity.

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1 Introduction

The shop scheduling problem considering transportation has been paid more attention to recently [1–3]. Due to their flexibility and efficiency, Automated guided vehicles (AGVs) have become an important transporting tool connecting the job processing between different machines in job shop. JSP-AGV was first studied by Bilge and Ulusoy using a sliding time-window heuristic algorithm to simultaneously schedule machines and AGVs to optimize makespan [4]. JSP-AGV is a highly complex

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problem combining two NP-hard problems: machine scheduling and AGV scheduling. Machines and AGVs are the two critical resources where machine performed the job processing, while AGV performed the job transportation between different machines.

Although research on JSP-AGV has become increasingly active, most existing studies assumed that AGVs have infinite battery capacity or can operate indefinitely. This assumption severely deviates from real-world operational scenarios. Under the constraints of limited battery capacity, frequent and time-consuming AGV charging directly interrupts transportation, changes AGV paths, and detours to charging so as to deactivate pre-existing scheduling solutions. Abderrahim notes that the job processing tasks, the AGV transport tasks and battery replenishment tasks are the three key problems for Flexible Manufacturing System (FMS) with AGVs [5]. Therefore, AGV charging is a critical factor that cannot ignored. Some studies have touched on related areas such as AGV scheduling with battery management [6,7], AGV scheduling in FMS with charging [8], and the location of battery charging storage in JSP-AGV [9]. However, current research on JSP-AGV rarely integrates AGV battery constraints within a JSP-AGV model. Consequently, there remains a significant gap in the literature concerning integrated scheduling models and optimization methods that simultaneously address job processing, AGV transportation, and battery charging constraints. This study aims to fill this gap by establishing a comprehensive JSP-AGV model with charging, thereby contributing to actionable scheduling for smart workshops deploying energy-constrained AGVs in practice.

The JSP-AGV scheduling is jointly determined by AGV transportation and job processing. Thus, the ratio of travel time to processing time determines whether the bottleneck lies in machine scheduling or AGV scheduling. When the ratio is low, AGV scheduling has a negligible impact on the overall scheduling, making machine scheduling the key issue. Conversely, when the ratio is high, AGV scheduling becomes the predominant factor. However, current research often oversimplifies this dynamic by considering only two scenarios, typically differentiating them based on whether the ratio is above or below a fixed threshold, for example, 0.25, as in the benchmark by Bilge and Ulusoy [4]. This binary classification warrants further, more nuanced investigation. Similarly, AGV quantity is a critical factor in JSP-AGV. Sufficient AGVs enable timely job delivery to machines for processing, making machine scheduling the key issue. Conversely, insufficient AGVs delay job delivery to machines, shifting the bottleneck to transportation. Most current studies focus on JSP with fixed number of AGVs, commonly two, or occasionally 1, 3, 4, 5, or 6 AGVs [10–14], yet they lack systematical analysis of how AGV quantity quantitatively impacts overall system performance.

Furthermore, a common oversight in existing research is the neglect of the initial transportation of jobs from the raw-material warehouse to machines and the final transportation from machines to the finished-product warehouse. These transportations are critical, as AGVs must perform them to complete the job delivery process. Therefore, the exit time (ET), which covers the whole production process, including the initial and final transportation, is a more comprehensive and precise performance metric for in JSP-AGV than makespan [15].

Although prior studies have advanced the understanding of JSP-AGV scheduling, two critical gaps persist. One gap is that the assumption of infinite AGV battery capacity overlooks the disruptive impact of charging processes on scheduling; the other is that the combined effects of travel time to processing time ratio, AGV quantity, and AGV battery capacity are not systematically analyzed. To address these gaps, this study formulates a novel integrated scheduling model that simultaneously coordinates machine scheduling, AGV scheduling, and battery replenishment decisions under charging constraints. The primary objectives are as follows:

(1) A mathematical formulation is developed that explicitly models the dynamic interaction between battery state-of-charge (SoC), AGV availability, and job start times.
(2) The GA algorithm is improved to solve the JSP-AGV with charging to minimize the ET.
(3) Design of experiments (DOE) is conducted to quantify the impact of travel-to-processing time ratio, AGV quantity and battery capacity on system performance.

By achieving these objectives, this work aims to move beyond conventional scheduling paradigms and provide a decision-support framework for truly autonomous and sustainable flexible manufacturing systems.

The rest of this paper is organized as follows. The related works are reviewed in Section 2. The model of JSP-AGV with charging is established in Section 3. The improved GA algorithm is devised in Section 4. Experiments are conducted and analyzed in Section 5. Finally, the conclusion and future prospects are summarized in Section 6.

2 Literature Review

Since Bilge introduced the JSP-AGV problem and the benchmark instances, most subsequent research on JSP-AGV employed metaheuristic algorithms to solve it. Ulusoy et al. proposed a GA to optimize makespan employing a fixed-length string encoding where each gene contains two codes representing a job operation and an AGV; however, one scheduling could be represented using multiple chromosomes leading to redundant search [16]. To overcome this limitation, Deroussi et al. proposed a vehicles-based encoding method to significantly reduce the search space [15]. Abdelmaguid devised a hybrid GA based on operation coding to optimize the makespan of JSP-AGV, incorporating a greedy heuristic rule of earliest processing time for AGV scheduling [17]. Gnanavel employed a Differential Evolution (DE) algorithm for JSP-AGV [18]. But similar to Abdelmaguid, the greedy heuristic rules resulted in a local optimal solution for AGV scheduling. Zheng et al. investigated a Tabu Search (TS) algorithm with two-dimensional encoding and neighborhood search to simultaneously schedule machines and AGVs for large-size problems [19]. Ham proposed a constraint programming and a medium-scale benchmark instance for scheduling transfer robot tasks in job shop, modelling both machine and mobile robot as constraining resources [20]. Abderrahim et al. devised a Variable Neighborhood Search (VNS) algorithm to optimize jobs and transportation tasks for makespan [21].

Mixed Integer Linear Programming (MILP) is often used to establish the model of JSP-AGV. El Khayat et al. used OPLStudio to solve the MILP model for JSP-AGV, but the travel time of the first operation from the warehouse to the machine is ignored [22]. Fontes uses chained decisions for machines and AGVs to reduce the number of variables and constraints in the MILP model, and employs the GUROBI solver to solve it [23]. Huang established a novel subscript-indexed MIP formulation, incorporating an AGV scheduling strategy based on network-optimized, and adopted CPLEX to solve the problem [24]. However, these models suffer from incomplete or over-constrained conditions. To address these limitations, Yao et al. proposed an MILP of JSP-AGV based on a modified disjunctive graph model that represents both transportation tasks and processing tasks [25]. Fontes et al. proposed a MILP model of JSP-AGV with part feeding, storage and retrieval, and devised a hybrid Simulated Annealing (SA) algorithm to solve larger instances [26]. Lacomme et al. introduced a framework based on an oriented disjunctive graph of JSP-AGV, and a memetic algorithm was devised to optimize both makespan and ET, and discovered new upper bounds [27]. Baruwa proposed Timed Colored Petri Net (TCPN) models for JSP-AGV, and an Anytime Layered Search (ALS) algorithm that combines breadth-first iterative deepening with sub-optimal breadth-first branch-and-bound and backtracking is devised to solve the problem [28].

Additionally, Deroussi and Norre extended the JSP-AGV benchmark instances established by Bilge and Ulusoy to FJSP-AGV by introducing additional machines [29]. Subsequently, Zhang et al. further extended these instances to a more general JSP with various characteristics, such as FMS, and Robotic Cells (RC), etc., and proposed a hybrid GA with Tabu search to optimize makespan [30]. Meng et al. devised an improved GA to solve the FJSP-AGV [31]. Pan et al. proposed a learning-based multi-population evolutionary optimization algorithm for FJSP with finite transportation resources [1]. Furthermore, for the dynamic scheduling problem of machines and AGVs, Xin et al. proposed a novel multi-objective genetic programming (GP) [32].

Beyond classical JSP-AGV, some extended variants of JSP-AGV have been studied. Chawla et al. studied the scheduling of multi-load AGVs in FMS using an improved memetic particle swarm algorithm to optimize travel time and waiting time [33]. Maoudj et al. investigated a capacitated multi-AGV scheduling problem using a distributed multi-agent approach [34]. Zeng et al. studied the blocking JSP-AGV using a hybrid algorithm with a modified timetabling method and local search to optimize both makespan and ET [10]. Heger and Voss presented a new MILP for AGVs scheduling in a flexible reentrant blocking job shop [35]. Udhayakumar and Kumanan studied AGVs travel distance and backtracking movements using a hybrid ant colony algorithm with particle swarm optimization (PSO) [36]. Zhong et al. solved the scheduling problem of AGVs and cranes in container terminals, considering conflict-free path planning using GA-PSO with a fuzzy logic controller [37]. Huang and Hu tackled the JSP-AGV with variable processing time using stochastic programming [38]. Zhang et al. addressed the JSP-AGV with delivery and pickup using a discrete artificial bee colony algorithm [39]. Saidi-Mehrabad et al. studied JSP-AGV considering conflict-free constraints using a two-stage ant colony algorithm to minimize makespan [40]. He et al. developed a multi-objective scheduling model for JSP-AGV that considers processing time, setup time, and AGV transport, aiming to optimize makespan, machine idle time, and energy consumption of AGVs and machines [41]. Amirteimoori et al. studied a hybrid JSP-AGV considering conflict-free path planning, accounting for constraints including the finite AGVs, alternative process routes, and job reentry [42]. Lu et al. studied the shop scheduling problem with limited buffers to optimize makespan and energy consumption [43].

Xie and Allen reviewed the JSP with material handling and classifies it into three system scheduling problems: FMS, AGV, and robotic or advanced cellular manufacturing system [44]. Nouri et al. presented a classification scheme for the JSP with transportation (JSPT) based on seven criteria, such as transportation resource, job complexity, and routing flexibility, among others [45]. Qiu et al. reviewed the AGV scheduling and routing algorithms [46], while Le-Anh and De Koster surveyed the AGV systems control and design [47].

Notably, the JSP-AGV involving AGV charging constraints has rarely been studied, despite that the AGV charging is important for its availability. Existing related work exhibits significant limitations. Mousavi et al. studied multi-objective AGV scheduling in FMS, considering AGV charging; however, the recharged AGVs are randomly reassigned, and the ratio of travel time to processing time is not explicitly addressed [8]. Dehnavi-Arani et al. optimized the location of battery charging storage in JSP-AGV using the GAMES framework [9]. Wang et al. studied AGV path plan and scheduling problem, considering the AGV battery capacity and map complexity, but the AGV is assigned one task to a workstation without recharging [48]. Abderrahim notes that the three key problems for FMS with AGV are job processing to machines, job transportation by AGVs, and AGV battery replenishment

[5]. Although Dang investigated AGVs scheduling with battery management [6,7], a comprehensive model for JSP-AGV with charging constraints remains absent from the literature.

ET is a more suitable performance metric than makespan for JSP-AGV. This is because ET accounts for the complete production timeline, encompassing the initial transportation of jobs from the raw material warehouse to machines and the final transportation from machines to the product warehouse, both of which are essential parts of the AGV transportation task. However, only a limited studies focused on optimizing ET for JSP-AGV. Deroussi et al. were the first to explicitly adopt ET as the optimal objective for JSP-AGV [15]. Subsequently, Lacomme et al. optimized ET using a memetic algorithm [27]. Zeng et al. minimized ET in the blocking job shop problem with AGV [10], while Fontes et al. minimized ET in the JSP-AGV using hybrid PSO and SA [49].

Although AGV quantity as a critical paremeter in JSP-AGVs, the systematic analysis of AGV quantity in JSP-AGV scheduling remains limited. The majority of research continues to use the two-AGV configuration in the benchmark by Bilge, without deliberately varying this parameter to study its effect. Among the limited works that do consider AGV quantity, Lyu et al. investigated the impact of AGV quantity [50]. He et al. established the multi-objective scheduling model for JSP-AGV to optimize makespan, machine idle time and energy consumption [41], and analyzed the impact of the AGV quantity on system performance. Similarly, Li also studied JSP-AGV considering AGV quantity [51].

In summary, prior research provides a solid foundation for JSP-AGV, but two critical gaps persist. First, the prevalent assumption of infinite AGV battery capacity overlooks the disruptive impact of charging processes on scheduling. Second, the combined effects of the travel time to processing time ratio, AGV quantity, and AGV battery capacity have not been systematically analyzed. Consequently, the core challenge addressed in this work is not the classical JSP-AGV, but the more complex JSP-AGV with AGV charging constraints, which necessitates integrated modelling and optimization. Furth more, the influence of travel time to processing time ratio on the system bottleneck of JSP-AGV requires systematical analyses. Additionally, the initial and final transportations of jobs, as an integral part of both the production process and AGV transportation tasks, must be considered in the overall scheduling. These factors are highly interdependent, yet existing research remains fragmented and often addresses them in isolation. Therefore, to address these gaps, this study established a comprehensive JSP-AGV model with charging constraints and the ratio of travel time to processing time. And a hybrid GA is devised to simultaneously schedule machine and AGV to optimize ET. Finally, orthogonal experiments are conducted to analyze the effects of travel-to processing time ratio, AGV quantity, and AGV charging on system performance.

3 JSP-AGV with Charging

3.1 Descriptions of JSP-AGV with Charging

The JSP-AGV problem with charging exhibits significant and inherent complexity. First, it essentially constitutes an integration of the classical JSP and AGV routing problem, both of them are NP-hard. A strong coupling exists among machine scheduling, AGV transportation routes, and charging decisions. For instance, the operation processing start time of a job depends on its preceding operation completion, its delivery by an AGV and the available time of the machine. Conversely, an AGV delivery schedule is constrained by its battery state, which dictates mandatory and time-consuming replenishment tasks. This interdependence creates a closed-loop dependency in the processing sequence, transportation route, or charging timing. Second, the introduction of charging constraints incorporates the dynamic consumption and replenishment of a continuous resource (battery power). AGVs thus become a contested resource not only for job transport but also for charging station occupancy. This induces a critical trade-off: dispatching an AGV for a transport task may improve machine utilization but risk battery depletion, while sending it to charge ensures future availability but incurs immediate transportation delay. Scheduling must resolve this conflict between transportation urgency and energy urgency in real time. This multi-level, multi-resource, and strongly coupled nature results in an extremely vast and complex solution space. Consequently, solving industry-scale problems within acceptable timeframes using traditional operations research methods such as MILP is computationally intractable. Therefore, it is necessary to design efficient metaheuristic algorithms.

The JSP-AGV in Fig. 1 is described: n jobs are processed on m machines, and each job consists of d operations, where d does not exceed m. Each operation is performed on one machine, and the jobs are transported between the loading/unloading stations and the machines by K AGVs. Each transportation task is divided into empty travel and loaded transport subtasks. AGV first travels empty from its current location to the original machine where the job is located. AGV waits at the original machine until the previous operation of the job processed, and then transports the job to the destination machine for the next operation. After the completion of a transport task, the battery level is assessed. If the AGV battery level is above the charging threshold, the AGV continues to the original machine for the next task, or it detours to the charging station for a full recharge and then continues to transport a job.

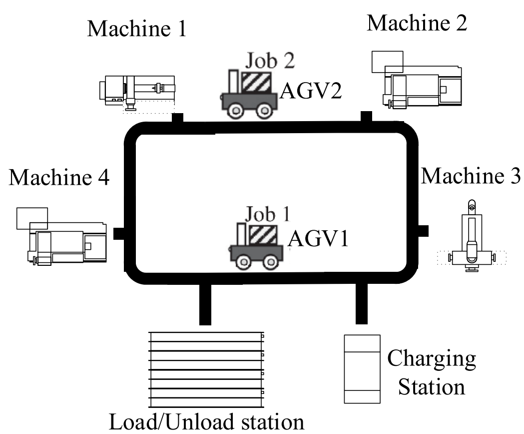

Figure 1: Diagram of JSP-AGV

Two primary AGV charging approaches are battery swapping and stationary charging. Battery swapping is faster but higher cost, while stationary charging takes a longer time but lower cost. Both approaches involve time consumption; charging duration is adopted in this paper. The dynamic fluctuation in the number of available AGVs during charging substantially increases the scheduling complexity. To reduce the complexity, the available time of AGVs is adopted to represent the charging status; i.e., the available time and location of AGVs are updated upon charging completion. The AGV will start the next transportation task from the charge station to the original machine. This approach effectively avoids the dynamic changes in the AGVs fleet size, thereby simplifying the scheduling problem.

3.2 Problem Assumptions and Notation

Some assumptions in JSP-AGV with charging are as follows. And notations are shown in Table 1.

1. JSP-AGV comprises n jobs, m machines, k AGVs, a raw material warehouse, a product warehouse and a charging station.
2. Jobs and AGVs are ready in the raw material warehouse at the beginning, while in the production warehouse upon completion.
3. Each job comprises d sequentially processed operations.
4. Each operation of a job is processed only once on each machine.
5. Machines and AGVs operate without breakdown.
6. Each operation is processed without interruption.
7. The machine processes only one operation at any given time.
8. The buffer of the machine is zero.
9. AGVs are identical, each with one unit load capacity and a constant speed.
10. The battery capacity of an AGV is sufficient to the charging station from any location when the battery level is at or below the predefined threshold.
11. AGV Charging continues without interruption until the battery is fully replenished.

Table 1: Notations in JSP-AGV

Notation	Description
J	Job
n	Job number
i	Job indices
J_i	Job i
O	Operation
d	Operation number
j	Operation indices
O_{ij}	The jth operation of job i
p_{ij}	Processing time for O_{ij}
M	Machine
m	Machine number
M_{ij}	The machine processing operation O_{ij}
A	AGV
k	AGV number
w	AGV indices
S_{ij}	Start processing time of O_{ij}
C_{ij}	Completion time of O_{ij}
C_i	Completion time of job i
$task_{ijw}$	Transportation task of O_{ij} from $m_{i(j-1)}$ to m_{ij} by AGV w
$T_{ijw\text{-}total}$	Total time of A_w for $task_{ijw}$
$T_{ijw\text{-}u}$	Unload travel time of A_w for task_{ijw}
$T_{ijw\text{-}load}$	Load travel time of $task_{ijw}$

(Continued)

Table 1 (continued)

Notation	Description
$T_{w\text{-}able}$	Available time of A_w
$T_{ij\text{-}w}$	Time that job i waiting for A_w
$T_{w\text{-}ij}$	Time that A_w waiting for job i
$T_{ijw\text{-}s}$	Start time of $task_{ijw}$
$T_{ijw\text{-}e}$	End time of $task_{ijw}$
$T_{w\text{-}pos\text{-}Mi(j-1)}$	Travel time of A_w from current position to $M_{i(j-1)}$
$T_{w\text{-}Mi(j-1)\text{-}Mij}$	Travel time of A_w from $M_{i(j-1)}$ to M_{ij}
$T_{Mij\text{-}station}$	Travel time of A_w from M_{ij} to charge station
$T_{i(d+1)w}$	Travel time of A_w from M_{id} to production warehouse
$P_{w\text{-}max}$	The max battery capacity of A_w
F_w	The indication flag for AGV charging
$P_{w\text{-}rate}$	The charging rate of A_w
$T_{w\text{-}chg}$	The charging time of A_w
P_{ijw}	The consumption power of A_w for $task_{ijw}$
$P_{threshold}$	The charging threshold of AGV
P_u	The consumption power of A_w without load
P_l	The consumption power of A_w with load
$P_{w\text{-}bat}$	The current battery capacity of A_w
ET_i	Exit time of job i
p_{avg}	The average processing time per operation
T_{avg}	The average travel time per transportation task
I_{agv}	The competition intensity of AGV
I_{mac}	The competition intensity of machine
m_e	Number of effective machine

3.3 The Model of JSP-AGV with Charging

While makespan is the primary performance metric in JSP, ET is a more suitable optimization objective for JSP-AGV. The critical distinction is that ET accounts for the complete production timeline, specifically including the final transportation to the product warehouse by AGVs. This final transportation is an integral and indispensable part of the overall transportation task, determining the time jobs leave the job shop. Thus, ET is adopted as the optimization objective for the comprehensive evaluation of JSP-AGV.

The objective and constraints for JSP-AGV with charging are as follows,

$$f = minMax(ET_i) \tag{1}$$

$$C_i = C_{id} = S_{id} + p_{id} \tag{2}$$

$$S_{ij} = C_{i(j-1)} + T_{ij-w} + T_{w-Mi(j-1)-Mij} \tag{3}$$

$$C_{ij} = S_{ij} + p_{ij} \tag{4}$$

$$T_{ijw-s} = \max\left\{T_{w-able} + T_{w-pos-Mi(j-1)}, C_{i(j-1)}\right\} \tag{5}$$

$$T_{ijw-e} = T_{ijw-s} + T_{w-Mi(j-1)-Mij} \tag{6}$$

$$T_{ij-w} = \begin{cases} T_{ijw-s} - C_{i(j-1)} & T_{ijw-s} > C_{i(j-1)} \\ 0 & \text{else} \end{cases} \tag{7}$$

$$T_{ijw-total} = T_{ijw-e} - T_{w-able} \tag{8}$$

$$T_{ijw-load} = T_{w-Mi(j-1)-Mij} \tag{9}$$

$$T_{ijw-u} = T_{ijw-total} - T_{w-Mi(j-1)-Mij} = T_{ijw-e} - T_{w-able} - T_{w-Mi(j-1)-Mij} \tag{10}$$

$$P_{ijw} = P_l * T_{ijw-load} + P_u * T_{ijw-u} \tag{11}$$

$$P_{w-bat}- = P_{ijw} \tag{12}$$

$$F_w = \begin{cases} 1 & P_{w-bat} < P_{\text{threshhold}} \\ 0 & \text{else} \end{cases} \tag{13}$$

$$T_{w-chg} = F_w * (P_{w-max} - P_{w-bat} - T_{Mij-station} * P_u)/P_{w-rate} \tag{14}$$

$$T_{w-able} = T_{ijw-e} + F_w * (T_{Mij-station} + T_{w-chg}) \tag{15}$$

$$ET_i = C_i + T_{i(d+2)w} \tag{16}$$

where the job and operation sequence is represented in constraints (2)–(4), constraint (2) defines complete time of job as the finish time of last actual operation, constraint (3) specifies that the start time of operation is constrained by the finish time of the preceding operation, the AGV arrival time, and the travel time between machines, constraint (4) represents the operation completion time is decided by start time and processing time, AGV transportation logic is represented in constraints (5)–(10), constraint (5) represents that the start time of task using AGV depends on the AGV availability time, the arrival time for AGV from previous job destination to current destination, and the completion time of the preceding operation, constraint (6) represents the complete time of one transportation task using AGV, constraint (7) represents the waiting time of job for AGV, constraint (8) represents the total time of AGV including waiting time, unloaded travel time, and loaded travel time, constraint (9) represents the loaded travel time of AGV, constraint (10) represents the unloaded travel time of AGV including waiting time, AGV battery charging is represented in constraints (11)–(15), constraint (11) represents the battery consumption of AGV for one task, constraint (12) represents the remaining charge of AGV, constraint (13) indicates the charging flag whether AGV detours to charging station, where $P_{\text{threshold}}$ is the AGV charging threshold which is set according to consumption power from the farthest machine to the charging station, constraint (14) represents the AGV charging time, constraint (15) represents the available time of AGV, and constraint (16) represents the exit time that job has been completed and transported to product warehouse.

The proposed formulation extends and integrates the two classical JSP models. It inherits the precedence and machine constraints from classical JSP formulations, while relaxing the assumption of immediate job availability after a preceding operation completes, as job transfer now depends on AGVs. Crucially, it extends the existing JSP-AGV models, which predominantly assume infinite AGV battery or ignore AGV charging entirely by introducing AGV battery capacity as a first-class dynamic state variable that couples the scheduling of processing, transportation and replenishment.

3.4 Bottleneck Analysis Based on Load Calculation and Resource Constraint

In JSP-AGV, machines are heterogeneous resources that job is processed on a specific machine, while AGVs are typically homogeneous resources performing identical transport functions. The transportation task number equals the operation number plus one for the final delivery to the ET. Theoretically, the system bottleneck is determined by the travel time-to-processing time ratio determines. It can be formalized by analyzing the machine competition intensity I_{mac} in Eq. (17) and the AGV competition intensity I_{agv} in Eq. (18), where the number of effective machines m_{e} is directly related to load distribution. The bottleneck of JSP-AGV shifts when AGV competition intensity overall the machine competition intensity. When I_{agv} is bigger than I_{mac} and $R_{\mathrm{tp}} = T_{\mathrm{avg}}/p_{\mathrm{avg}}$ is substituted, the constraint (19) indicates the bottleneck of JSP-AGV.

$$I_{mac} = N * d * \frac{p_{avg}}{m_e} \tag{17}$$

$$I_{agv} = N * (d + 1) * \frac{T_{avg}}{k} \tag{18}$$

$$R_{tp} = \frac{T_{avg}}{p_{avg}} > \frac{d + 1}{d} * \frac{k}{m_e} \tag{19}$$

4 Improved GA

The GA is well-suited for JSP-AGV due to its population-based, flexible, and parallelizable nature. The chromosome representation provides an intuitive and flexible structure to encode the complex, composite solution comprising job sequence and AGV assignment. The crossover operator enables the recombination of high-quality blocks from parents, allowing the search to efficiently explore promising regions. The population-based method can guide the depth and breadth of the search with high efficiency. Thus, an improved GA (IGA) is proposed to optimize the ET of JSP-AGV with charging. The IGA framework is shown in Fig. 2, where OS represents the operation segment chromosome, while AS represents the AGV segment chromosome. First, a novel chromosome encoding as a unifying representation is devised. Unlike standard JSP or AGV scheduling encodings, our two-segment chromosome simultaneously encodes job permutation and AGV scheduling. This ensures the job scheduling and AGV scheduling simultaneously are optimized. Then, problem-specific operators for guided search is devised. The different operators are devised for the operation chromosome and the AGV chromosome. This means the search explores the solution space where high-quality machine schedules and AGV schedules coexist. Finally, a decoder mechanism is proposed in which the job and AGV are simultaneously scheduled under AGV charging constraints. This mechanism resolves conflicts between AGV availability and AGV charging events during decoding.

4.1 Two-Segment Chromosome Encoding

A two-segment chromosome encoding scheme is adopted to simultaneously represent machine scheduling and AGV scheduling, in which operation-based encoding is for processing sequences and AGV-based encoding for transportation assignments. A fundamental mismatch arises because the total number of required AGV transports from raw material storage, between machines and to finished product storage exceeds the number of processing operations. Specifically, the length of operation-based encoding is one unit less than that of AGV-based encoding to complicate a unified encoding structure. To resolve this discrepancy and establish a consistent and simplified encoding framework, virtual final operations and virtual machines are introduced. A virtual operation is an additional operation with zero processing time appended to each job, and the production warehouse is treated as a virtual machine for the virtual operation. This design ensures that the operations and transportation tasks have identical lengths (both $d + 1$). Consequently, both chromosomes enable a symmetrical encoding structure. The total virtual operations number equals the total jobs number.

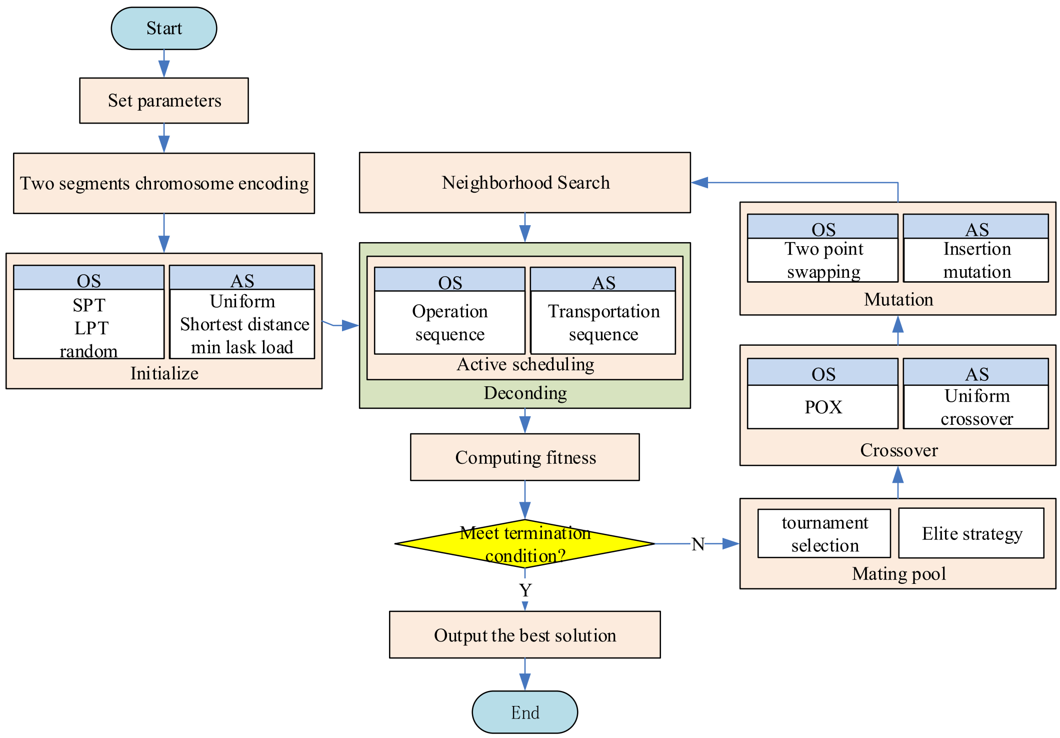

Figure 2: Framework of IGA

Both the operation encoding and the AGV encoding adopt integer-based encoding. Operation encoding is a job-based representation. Each gene is an integer representing the job index, and the k-th occurrence of the job represents its k-th operation in the chromosome. Similarly, the AGV encoding consists of AGV indices. Each gene indicates the AGV assigned to the transport job for the operation located at the corresponding position in the operation chromosome.

Fig. 3 illustrates an encoding example involving three jobs with two real operations and three AGVs. In the operation encoding segment, each gene is a job identifier, and their order on the chromosome represents the operation order. Each job appears three times in the chromosome. The first two represents real operation on machines, while the third is a virtual operation O_{i3} on the virtual machine M_3, which corresponds to the finished product warehouse. The transportation task sequence is derived from the operation encoding. The subscripts of each transportation tasks indicate the starting and ending positions. Specifically, 0 represents the raw material warehouse, 3 represents the finished product warehouse, and other numbers indicate the specific machines. Each code in the AGV encoding segment represents an AGV identifier, and the transportation task of operation is assigned to the AGV at the same position in the AGV encoding.

For example, the first gene "3" in the operation encoding represents the first operation O_{31} of job 3 on machine M_1. The corresponding transportation task T_{01} from the raw material warehouse to machine M_1 is assigned to AGV 1. The second gene "3" in the operation encoding represents the second operation O_{32} of job 3 on machine M_2. The transportation task T_{12} from machine M_1 to machine M_2 is assigned to AGV 2. The third gene "3" in the operation encoding represents the virtual process O_{33}

of job 3 on virtual machine M_3 (finished product warehouse). The final transportation task T_{23} from machine M_2 to the finished product warehouse is assigned to AGV 3.

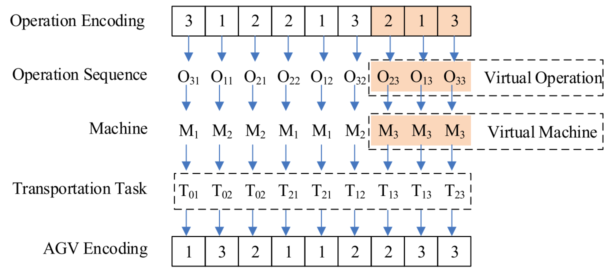

Figure 3: Encoding of two segments chromosome

4.2 Population Initialization

Population initialization plays a guiding role in the algorithm search process, and high-quality initial solutions can effectively improve solution efficiency. Based on the characteristics of JSP-AGV, we adopt a hybrid method combining a random method and heuristic rules to ensure both solution quality and population diversity. The hybrid initialization strategy is deliberately designed to leverage the complementary strengths of different methods to generate a high-quality and diverse initial population. The Shortest Processing Time (SPT) rule prioritizes jobs with shorter operations, effectively reducing work-in-process inventory and average job completion time locally. Conversely, the Longest Processing Time (LPT) rule prioritizes longer processing time jobs, which helps prevent long jobs from being excessively delayed, resulted in critical bottlenecks. SPT and LPT represent two fundamentally different and competing scheduling strategies. These two rules ensure the initial population spans the solution space. Random initialization ensures sufficient diversity and unbiased exploration of the vast solution space, preventing premature convergence. Random initialization 50%, Shortest Processing Time (SPT) 30%, and Longest Processing Time (LPT) 20% are used to initialize machine scheduling to improve search efficiency and avoid local optima. Uniform distribution, shortest distance to the transportation task's starting point, and minimum task load are used to initialize AGV assignment to enhance the utilization efficiency.

4.3 Selection

The tournament selection is adopted due to low computational complexity and easy parallelization. During selection, a subset of solutions is randomly chosen for reproduction. Additionally, an elite strategy is adopted to save the best solution and accelerate convergence; the top 3% individuals with the highest fitness will be copied to the next generation at the end of each generation, replacing the worst 3% individuals, which ensures that the genetic search does not regress and population diversity for continued exploration.

4.4 Crossover

New offspring chromosomes are generated by exchanging genes from two parent chromosomes. For the operation encoding segment, the Precedence Operation Crossover (POX) is adopted, in which the advantages of the parent individuals are effectively preserved [52].

1. The job set $\{J_1, J_2, \ldots, J_n\}$ is randomly divided into two subsets: Jobset1 and Jobset2
2. Two offspring, C1 and C2, are generated from the two job subsets.

As illustrated in Fig. 4, job set is {1, 2, 3, 4, 5}, and Jobset1 is {1, 3}, and Jobset2 is {2, 4, 5}. The offspring C1 is generated from Jobset1 by sequentially copying genes from the parent chromosomes. The genes in parent chromosome P1 that belong to Jobset1 are copied to the same position in C1. Then, the remaining vacant positions in C1 are filled in order with the genes from parent chromosome P2 that do not belong to Jobset1. Similarly, offspring C2 is generated from Jobset2 using the same method.

For the AGV encoding segment, the uniform crossover operator is employed, in which a randomly generated binary mask with the same length of chromosome determines the exchange pattern, and the genes are exchanged at positions marked ‘1’ between parent chromosomes while unchange at positions marked ‘0’.

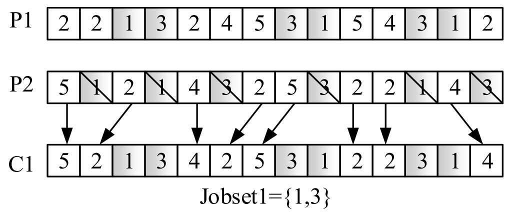

Figure 4: POX

4.5 Mutation

The two-point gene swapping mutation operator is used for the operation encoding. The two random genes are exchanged in the chromosome. This approach ensures the encoding legality while the mutation performed.

An insertion mutation is employed for the AGV encoding. First, two distinct positions are randomly selected, then the gene at the latter position is inserted before the former, with the intermediate genes are shifted sequentially backward. This displacement introduces localized modifications while preserving AGV resource allocation validity.

4.6 Neighborhood Search

Neighborhood search is performed on the top 3 solutions. 3 different positions are randomly selected in the individual, the genes at these three positions are permuted to generate 5 additional candidate solutions, then the best one is selected to replace the original solution.

4.7 Decoding

The decoding process translates the operation and AGV chromosomes into an active scheduling. It proceeds sequentially through each gene in the operation and AGV encoding.

1. One gene in the operation chromosome is sequentially converted into the corresponding operation O_{ij}, and its information is obtained.
2. The transportation task information of operation is obtained, including the start point (current machine), destination (machine for next operation) and travel time.
3. The corresponding gene in the AGV chromosome is assigned for the transportation task, and the status of the AGV is obtained.
4. The travel time $T_{w\text{-pos-}mi(j-1)}$ for AGV to the task start point is obtained, the start time $T_{ijw\text{-}s}$ of $task_{ijw}$ is calculated using Eq. (5), while the end time $T_{ijw\text{-}e}$ of $task_{ijw}$ using Eq. (6).

5. The start time S_{ij} for operation O_{ij} is calculated using Eqs. (3) and (7), and the complete time C_{ij} for operation O_{ij} using Eq. (4), then the active scheduling scheme for operation O_{ij} is generated.
6. The load time $T_{ijw\text{-}load}$ is calculated using Eq. (9) and the unload time $T_{ijw\text{-}u}$ of $task_{ijw}$ using Eqs. (8) and (10), the consumption power P_{ijw} for $task_{ijw}$ using Eq. (11), and the current AGV battery capacity $P_{w\text{-bat}}$ using Eq. (12).
7. The transportation task $task_{ijw}$ is performed.
8. Determine whether the AGV detours to charge according to Eq. (13). If not, skip to Step 9; else AGV detours to charging station for a full recharge, the charging time $T_{w\text{-}chg}$ time is calculated using Eq. (14).
9. The AGV available time is calculated using Eq. (15), and the status of AGV is updated.
10. Determine whether the decoding process is completed. If not, skip to Step1; if it does, end.

5 Experiments

Experiments are programmed in C++ and performed on Thinkpad T470P with Core i7-7700HQ, 32 G Ram and Windows 10. The algorithm parameters are 200 individuals in population, crossover probability of 0.8, mutation rate of 0.01, and 200 generations. These parameters are widely adopted in the evolutionary computation community as robust default settings that balance exploration and exploitation [52]. And the value was averaged over 10 experiments.

AGVs and machines are the critical resources for transporting and processing jobs and have a strong coupling relationship. The ET is determined by both travel time and processing time. The system bottleneck in transportation or processing is determined by the ratio of travel time to processing time. Therefore, a thorough investigation of the ratio's impact on scheduling performance is essential.

The travel time between two machines is proportional to the distance for AGVs at a constant speed. To accommodate various scenarios, the distance between adjacent machines is assumed as a unit distance, and the travel distance between any two machines can be represented by the absolute difference of machine indices. Consequently, the travel time can be expressed as:

$$T = R_c * |m_i - m_j| \tag{20}$$

where R_c is a time coefficient with a default value of 1. The value of R_c can be adjusted to control the ratio of travel time to processing time, thereby evaluating the impact on scheduling performance. The charging station and the raw material warehouse are both located at position 0, while the machines position are numbered starting from index 1, and the product warehouse, as a virtual machine, is situated at the final position.

As a typical instance and moderate difficulty for JSP, FT10 is selected to validate the model of JSP-AGV and the algorithm. In FT10, each job with 10 operations is processed on 10 machines. The operation processing time ranges from 2 to 99 units, resulting in the average processing time of approximately 51 units per operation. For our experiments, the coefficient R_c in Eq. (20) is set to 1; then, the travel time between machines ranges from 1 to 11 units, yielding the total travel time of 318 units across 110 transportations, and an average travel time of 2.9 units per trip.

In experiments, the six key performance metrics are analyzed to comprehensively evaluate the scheduling. *ET* is the exit time of jobs, *chargeNum* is the average number of charges per AGV, *waitMac* is the ratio of jobs waiting time for machines to ET, indicating that jobs arrive while machines are occupied. The lower value suggests a reduction in machine bottlenecks, reflecting an alleviation of machine resources. *macWait* is the ratio of the machines waiting time for jobs to ET, indicating machine idle time. The higher value indicates greater machine idleness, underutilization of machines. *agvWait* is the ratio of AGVs waiting time for jobs to ET, indicating that AGVs arrive at the machine before operation completion. The higher value implies sufficient AGV transport capacity relative to demand. *waitAGV* is the ratio of jobs waiting time for AGVs to ET, indicating that the operation is completed before the AGV arrival. The higher value suggests insufficient AGV availability, highlighting a potential bottleneck in job transportation.

5.1 ET Analysis of the Ratio of Travel Time to Processing Time

To better study the influence of the ratio, assuming that AGV battery capacity is enough without charging temporarily, and 10 AGVs are used to transport jobs without delay. Consequently, both *chargeNum* and *waitAGV* metric values are zero.

To systematically evaluate the interaction between travel time and processing time, the symmetric ratio spectrum is established. This spectrum comprises nine discrete values for the ratio $R_{\text{tp}} = T_{\text{avg}}/p_{\text{avg}}$: 0.1, 0.2, 0.5, 0.75, 1, 1.5, 2, 5, and 10. The corresponding time coefficient values, $R_{c,}$ are 2, 4, 10, 15, 20, 30, 40, 100, 200, respectively. This design ensures mathematical symmetry between the travel-to-processing time ratio R_{tp} and its reciprocal processing-to-travel time ratio ($1/R_{tp}$). The unity ratio ($R_{tp} = 1$) serves as the central symmetric reference point. The values are distributed to span multiple orders of magnitude from 0.1 to 10 in a roughly logarithmic progression, maintaining proportional consistency in both ratio directions. This symmetric ratio framework facilitates rigorous examination of temporal parameter influences while maintaining mathematical consistency across all experimental conditions.

The change-point is detected using the Pruned Exact Linear Time (PELT) algorithm and illustrated in Fig. 5, plotted on a logarithmic x-axis. The significant transitions across all curves are consistently and labelled with a star at R_{tp} is 1.5. This critical threshold indicates a fundamental paradigm shift in the scheduling problem. When $R_{tp} < 1.5$, the JSP-AGV problem primarily manifests as a job shop scheduling challenge dominated by machine constraints, while when $R_{tp} \geq 1.5$, the problem transforms into an AGV-centric scheduling optimization like TSP. It is important to contextualize this finding. In this specific experiment, the number of operations, AGVs and machines is all 10. Considering that the typical machine load rates in a job shop range from 60% to 85%, and according to the theoretical analysis in Constraints (19), the corresponding R_{tp} range is calculated to be 1.3 to 1.8. The experimentally observed transition at $R_{tp} = 1.5$ falls squarely within this theoretical range, confirming the consistency between our experimental results and qualitative theoretical analysis. Notably, this critical ratio ($R_{tp} = 1.5$) was observed under conditions of ideal AGV availability (10 units). In real-world implementations with fewer AGVs, this phenomenon stems from reduced AGV quantities, which amplify transportation latency. And potentially altering the operational characteristics of the system. This suggests that the identified threshold of 1.5 represents an upper bound under ideal resource conditions.

The ratio of travel time to processing time becomes as the primary factor affecting JSP-AGV system bottlenecks because it directly determines the critical condition of bottleneck transfer between the machine processing system and AGV transportation system. When R_{tp} is low, the processing time is much longer than the travel time. The AGV can quickly complete the job transportation and then idle while the processing machine is the sole system bottleneck, and the core of scheduling optimization is the machine scheduling. Although the charging constraint of AGV increases the complexity, it does not change the fundamental of the bottleneck. When R_{tp} increases to exceed the critical threshold (1.5), the transportation time will be close to or greater than the processing time. AGVs need more time to perform the transportation while the machines are idle for a job. At this time, AGVs become a competitive bottleneck resource. Any delay, such as from mandatory charging, will directly block the subsequent processing operations. The system shifts from a 'machine-led' to an 'AGV led' paradigm. Of course, the 'machine-AGV coupling' bottleneck mode is between the 'machine-led' to 'the AGV led' bottleneck mode. Therefore, the R_{tp} ratio is a key lever that dictates the bottleneck nature of JSP-AGV. This study quantifies its primary influence through experiments and verifies the continuation and deepening of classical scheduling theory in the new generation of integrated and AGV battery capacity constrained manufacturing systems.

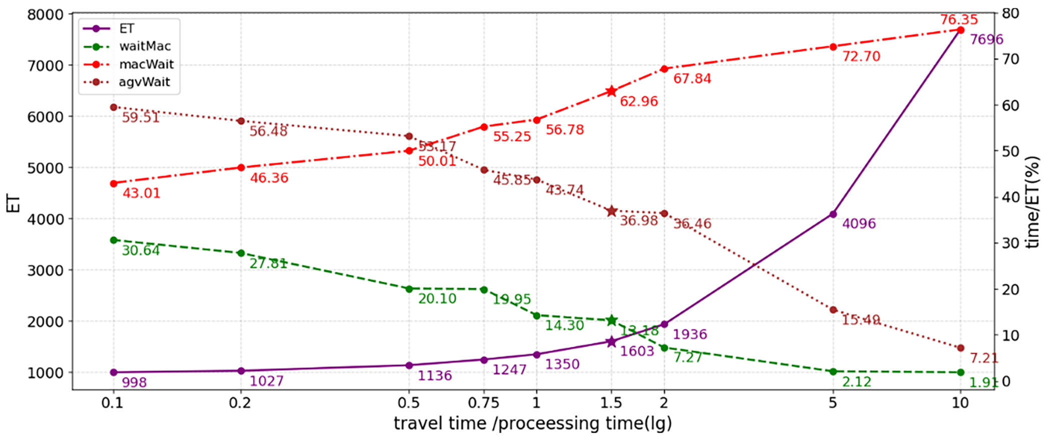

Figure 5: ET at different ratio of travel time to processing time

5.2 Orthogonal Experiments

A three-factor (AGV quantity, battery capacity, and ratio) five-level orthogonal experimental design was implemented to systematically investigate their impacts on the six key performance metrics.

In the orthogonal experimental design, AGV quantities were discretely sampled within the range of [1, 10] to ensure AGV fleet scalability. Based on the critical ratio threshold of $R_{tp} = 1.5$ identified in the previous analysis (Section 5.1), the five ratio levels are set below the transition point. Due to the presence of the variable ratio, the travel time and the energy consumption of AGVs varied accordingly. AGV energy consumption is modeled with loaded power consumption being five times that of the unloaded (no-load) state. Considering the charging threshold and redundancy, the battery capacity was set to 1.5 times the loaded energy requirement. The 3-factor 5-level value is shown in Table 2. And results are shown in Table 3.

Table 2: The 3-factor 5-level value

Factors	Level				
	1	2	3	4	5
AGV quantity	3	5	7	8	9
Battery capacity	2000	3000	4000	6000	8000
Ratio	0.2	0.5	0.75	1	1.5

Table 3: The orthogonal experimental results

No.	AGV quantity	Battery capacity	Ratio	ET	chargeNum	waitMac	macWait	waitAGV	agvWait
1	3	2000	0.20	1590	1.00	13.79	58.08	40.03	42.43
2	3	3000	0.50	2543	1.33	7.81	71.65	70.66	23.21
3	3	4000	0.75	3934	1.67	3.92	73.55	77.49	20.56
4	3	6000	1.00	4383	1.00	2.34	80.35	77.36	11.04
5	3	8000	1.50	6231	1.33	1.06	80.98	83.82	9.61
6	5	2000	0.50	2208	1.80	8.21	66.70	64.56	37.91
7	5	3000	0.75	2506	1.40	9.79	69.13	56.95	28.34
8	5	4000	1.00	3209	1.00	4.79	74.08	59.99	18.28
9	5	6000	1.50	4654	1.00	1.83	79.55	69.95	20.13
10	5	8000	0.20	1221	0.00	16.04	53.73	32.56	66.04
11	7	2000	0.75	2599	1.71	6.49	67.73	59.22	32.91
12	7	3000	1.00	2829	1.14	8.18	72.76	54.58	25.98
13	7	4000	1.50	3863	1.43	2.19	75.04	76.96	23.95
14	7	6000	0.20	1131	0.00	19.47	51.30	22.30	72.87
15	7	8000	0.50	1526	0.00	15.04	62.50	33.03	54.77
16	8	2000	1.00	2891	2.00	7.89	73.18	55.73	27.14
17	8	3000	1.50	4167	1.63	1.73	74.09	59.10	22.92
18	8	4000	0.20	1134	0.00	17.69	49.44	23.02	71.89
19	8	6000	0.50	1458	0.00	15.72	60.07	30.02	54.64
20	8	8000	0.75	1688	0.00	11.45	64.85	35.91	44.77
21	9	2000	1.50	4186	2.56	5.70	76.95	65.11	25.86
22	9	3000	0.20	1137	0.00	21.05	54.16	18.78	75.05
23	9	4000	0.50	1416	0.00	15.71	53.47	23.03	54.06
24	9	6000	0.75	1691	0.00	10.57	64.88	34.68	47.86
25	9	8000	1.00	1916	0.00	9.80	67.63	30.96	41.58

Range analysis and analysis of variance (ANOVA) are used to analyze the results. Range analysis provides an intuitive assessment of factor influence, by which the influence degree of various factors is evaluated on the results. While ANOVA can eliminate the interference of experimental errors and investigate the significance levels of variables on experimental results. Specifically, range analysis prioritizes factors by comparing the magnitude of level differences, while ANOVA quantifies the statistical significance of variables through F-tests and p-values, with a typical significance threshold set at 0.05. This combined approach ensures both intuitive interpretation of factor impacts and rigorous statistical verification.

5.2.1 Analysis of ET

Range analysis of ET in Table 4 reveals that the ratio is the predominant influencing factor, secondarily by AGV quantity, whereas the impact of AGV battery capacity is completely negligible for its range value is lower than that of irrelevant factors. The ANOVA of ET in Table 5 further confirmed Ratio's statistical significance ($p < 0.05$) marked with $*$, neither AGV quantity nor battery capacity demonstrated statistically significant effects.

Table 4: Range value of ET

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	3736.200	2694.800	1242.600	2435.400	2436.600	2266.600
Level 2 Mean	2759.600	2636.400	1830.200	2441.800	2569.200	2767.250
Level 3 Mean	2389.600	2711.200	2483.600	2671.200	2725.600	2638.333
Level 4 Mean	2267.600	2663.400	3045.600	2747.000	2655.800	2757.200
Level 5 Mean	2069.200	2516.400	4620.200	2926.800	2835.000	2818.600
Range	1667.000	194.800	3377.600	491.400	398.400	552.000

Table 5: Variance of ET

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	8,715,272.960	4	1.168	2.780	
Battery capacity	119,056.960	4	0.016	2.780	
Ratio	33,592,842.960	4	4.504	2.780	$*$
Error	44,754,824.48	24			

5.2.2 Analysis of ChargeNum

Range analysis of *chargeNum* in Table 6 reveals that the AGV battery capacity is the predominant influencing factor, secondarily by Ratio, whereas the impact of AGV quantity is relatively minor. The ANOVA of *chargeNum* in Table 7 further confirmed AGV battery capacity statistical significance ($p < 0.05$) marked with $*$; neither AGV quantity nor the Ratio demonstrated statistically significant effects.

Table 6: Range value of *chargeNum*

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	1.266	1.814	0.200	0.628	0.726	0.766
Level 2 Mean	1.040	1.100	0.626	0.952	0.808	1.223
Level 3 Mean	0.856	0.820	0.956	1.020	1.074	0.778
Level 4 Mean	0.726	0.400	1.028	0.992	0.846	0.868
Level 5 Mean	0.512	0.266	1.590	0.808	0.946	0.854
Range	0.754	1.548	1.390	0.392	0.348	0.457

Table 7: Variance of *chargeNum*

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	1.672	4	0.623	2.780	
Battery capacity	7.659	4	2.852	2.780	*
Ratio	5.293	4	1.971	2.780	
Error	16.11	24			

5.2.3 Analysis of WaitMac

Range analysis of *waitMac* in Table 8 reveals that the Ratio is the predominant influencing factor, secondarily by AGV quantity, whereas the impact of AGV battery capacity is negligible for its range value is similar to that of irrelevant factors. The ANOVA of *waitMac* in Table 9 further confirmed Ratio statistical significance ($p < 0.05$) marked with $*$; neither AGV quantity nor battery capacity demonstrated statistically significant effects.

Table 8: Range value of *waitMac*

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	5.784	8.416	17.608	10.192	9.184	10.258
Level 2 Mean	8.132	9.712	12.498	8.900	8.724	9.443
Level 3 Mean	10.274	8.860	8.444	8.626	9.912	10.197
Level 4 Mean	10.896	9.986	6.600	10.112	9.048	8.462
Level 5 Mean	12.566	10.678	2.502	9.822	10.784	9.142
Range	6.782	2.262	15.106	1.566	2.060	1.796

Table 9: Variance of *waitMac*

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	138.119	4	0.968	2.780	
Battery capacity	16.244	4	0.114	2.780	
Ratio	666.101	4	4.668	2.780	*
Error	856.25	24			

5.2.4 Analysis of MacWait

Range analysis of *macWait* in Table 10 reveals that the Ratio is the predominant influencing factor, secondarily by AGV quantity, whereas the impact of AGV battery capacity is minor. The ANOVA of *macWait* in Table 11 further confirmed Ratio statistical significance ($p < 0.05$) marked with $*$; neither AGV quantity nor battery capacity demonstrated statistically significant effects.

Table 10: Range value of *macWait*

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	72.922	68.528	53.342	65.742	66.726	65.990
Level 2 Mean	68.638	68.358	62.878	67.696	67.200	68.495
Level 3 Mean	65.866	65.116	68.028	66.654	67.412	67.965
Level 4 Mean	64.326	67.230	73.600	67.674	68.220	65.874
Level 5 Mean	63.418	65.938	77.322	67.404	65.612	66.952
Range	9.504	3.412	23.980	1.954	2.608	2.621

Table 11: Variance of *macWait*

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	295.072	4	0.815	2.780	
Battery capacity	44.517	4	0.123	2.780	
Ratio	1773.433	4	4.900	2.780	$*$
Error	2171.43	24			

5.2.5 Analysis of WaitAGV

Range analysis of *waitAGV* in Table 12 reveals that the Ratio is the predominant influencing factor, secondarily by AGV quantity, whereas the impact of AGV battery capacity is minor. The ANOVA of *waitAGV* in Table 13 further confirmed Ratio statistical significance ($p < 0.05$) marked with $*$; neither AGV quantity nor battery capacity demonstrated statistically significant effects.

5.2.6 Analysis of AgvWait

Range analysis of *agvWait* in Table 14 reveals that the Ratio is the predominant influencing factor, secondarily by AGV quantity, whereas the impact of AGV battery capacity is minor. The ANOVA of *agvWait* in Table 15 further confirmed Ratio statistical significance ($p < 0.05$) marked with $*$; neither AGV quantity nor battery capacity demonstrated statistically significant effects.

Table 12: Range value of *waitAGV*

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	69.872	56.930	27.338	44.700	45.366	46.984
Level 2 Mean	56.802	52.014	44.260	54.118	50.762	54.515
Level 3 Mean	49.218	52.098	52.850	50.882	51.952	48.482
Level 4 Mean	40.756	46.862	55.724	51.094	54.714	50.254
Level 5 Mean	34.512	43.256	70.988	50.366	48.366	52.132
Range	35.360	13.674	43.650	9.418	9.348	7.531

Table 13: Variance of *waitAGV*

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	3834.178	4	2.260	2.780	
Battery capacity	557.711	4	0.329	2.780	
Ratio	5138.138	4	3.029	2.780	*
Error	10,179.46	24			

Table 14: Range value of *agvWait*

	AGV quantity	Battery capacity	Ratio			
Level 1 Mean	21.370	33.256	65.656	37.474	37.252	38.188
Level 2 Mean	34.140	35.100	44.918	37.646	37.944	35.055
Level 3 Mean	42.096	37.748	34.888	39.168	38.616	40.408
Level 4 Mean	44.278	41.308	24.810	38.380	38.544	37.394
Level 5 Mean	48.882	43.354	20.494	38.098	38.410	38.650
Range	27.512	10.098	45.162	1.694	1.364	5.353

Table 15: Variance of *agvWait*

Factor	SS	df	F-ratio	F-critical value	Significance
AGV quantity	2329.738	4	1.506	2.780	
Battery capacity	352.349	4	0.228	2.780	
Ratio	6513.582	4	4.209	2.780	*
Error	9284.16	24			

From the above analysis, the ratio of travel time to processing time has a predominant influence, AGV quantity has a certain influence, while AGV battery capacity has a little influence on time metrics, including the ET, *waitMac, macWait, waitAGV* and *agvWait*. This occurs because the ratio and AGV quantity jointly determine whether jobs are transported and processed in a timely manner. *chargeNum* is predominantly determined by AGV battery capacity and then secondarily by the Ratio.

5.3 Ablation Experiments

To verify the effectiveness of the improved strategy in IGA, the ablation experiments are conducted. The first instance from the orthogonal experiment was selected to compare the improvements. The best result of each algorithm is selected from ten independent experiments. The convergence curves are shown in Fig. 6. The results show that the exploration and exploitation of the algorithm is gradually enhanced by adding the improved strategy, and IGA converges on the best solution at the fastest speeds, thereby validating the synergistic effectiveness of the proposed enhancements.

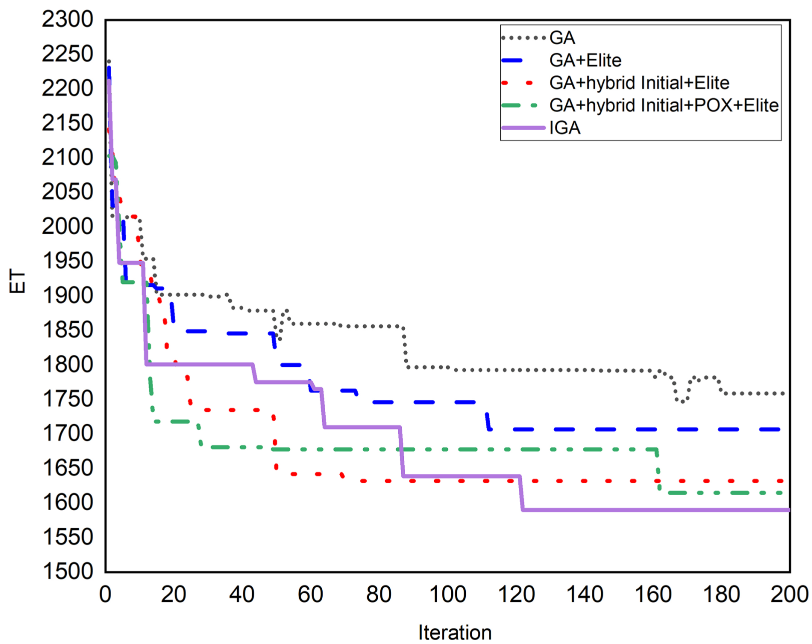

Figure 6: Convergence curve of optimization

5.4 Algorithm Comparison

The comparison experiments with other algorithms including GA, ACO (Ant Colony Optimization), PSO, DE and Gurobi solver are conducted to validate the model and algorithm. The results of orthogonal experiments in Table 16 show that IGA is superior to the comparison algorithm, where the best results are highlighted in bold.

Table 16: Comparison results among different algorithms

No.	AGV quantity	Battery capacity	Ratio	Gurobi	ACO	GA	PSO	DE	IGA
1	3	2000	0.20	1685	2168	1891	1945	1828	**1590**
2	3	3000	0.50	3192	3460	3243	3206	3222	**2543**
3	3	4000	0.75	4370	4479	4255	4324	4243	**3934**
4	3	6000	1.00	5700	5865	5658	5622	5673	**4383**
5	3	8000	1.50	8232	8174	7859	7904	7975	**6231**
6	5	2000	0.50	2304	2546	2322	2296	2239	**2208**
7	5	3000	0.75	3389	3233	3086	3225	3152	**2506**
8	5	4000	1.00	4107	4140	3954	3923	3844	**3209**
9	5	6000	1.50	6474	5676	5497	5429	5154	**4654**
10	5	8000	0.20	**968**	2119	1172	1145	1161	1221
11	7	2000	0.75	2836	2742	2627	2769	2671	**2599**
12	7	3000	1.00	3140	3364	3047	3093	**2819**	2829
13	7	4000	1.50	5105	4604	4329	4518	4162	**3863**

(Continued)

Table 16 (continued)

No.	AGV quantity	Battery capacity	Ratio	Gurobi	ACO	GA	PSO	DE	IGA
14	7	6000	0.20	**897**	1638	1015	1062	991	1131
15	7	8000	0.50	**1157**	2585	2363	2376	1391	1526
16	8	2000	1.00	2845	3070	2841	2961	**2796**	2891
17	8	3000	1.50	4321	4244	4216	4341	4214	**4167**
18	8	4000	0.20	1357	1590	1408	1409	1370	**1134**
19	8	6000	0.50	1812	2258	2081	2089	2034	**1458**
20	8	8000	0.75	2467	2855	2676	2655	2618	**1688**
21	9	2000	1.50	4191	4027	3879	3766	3711	4186
22	9	3000	0.20	1172	1418	1274	1243	1202	**1137**
23	9	4000	0.50	1858	2019	1849	1774	1815	**1416**
24	9	6000	0.75	2346	2645	2380	2410	2326	**1691**
25	9	8000	1.00	2622	3267	3039	2974	2896	**1916**

6 Conclusion

The novel JSP-AGV mode incorporating AGV charging is proposed. This advances the state of the art models with simplified energy assumptions by tackling the AGV charging constraints rather than treating charging as an afterthought or simplifying it away. And GA is improved to simultaneously and effectively handle the machine scheduling and AGV scheduling under the new charging constraints. The ET, which is jointly determined by AGV travel time and job processing time, is selected as the optimization objective for JSP-AGV with charging. This metric provides a more comprehensive evaluation of the JSP-AGV with charging considering AGV quantity, travel time and processing time.

A comprehensive experimental investigation is conducted to evaluate how the ratio of travel time to processing time influences shift in the scheduling bottlenecks using four metrics, including ET, machines' waiting time for jobs, jobs waiting time for machines, and AGVs' waiting time for jobs. Experiments with symmetric ratio spectrum with nine discrete values spanning decades (0.1–10) with logarithmic progression are conducted, and the change-points are identified at a ratio R_{tp} of 1.5 across all performance curves using the PELT algorithm. This critical threshold indicates a fundamental paradigm shift in the scheduling problem and represents an upper bound for the transition under conditions of sufficient AGV resources.

Furthermore, orthogonal experiments are conducted to quantify the effects of AGV battery capacity, AGV quantity, and the travel time to processing time ratio on six metrics including, ET, machines waiting time for jobs, jobs waiting time for machines, AGVs waiting time for jobs, jobs waiting time for AGVs, and AGVs charging number. The results using range analysis and ANOVA reveal that the AGV battery capacity is the predominant influencing factor, followed by ratio and then AGV quantity on the charging number metric, while the ratio is the predominant influencing factor, followed by AGV quantity and then AGV battery capacity on the other five metrics. This hierarchical influence can be mechanistically explained. The ratio determines whether the bottleneck of JSP-AGV is on machine scheduling or AGV scheduling. A low ratio signifies that processing times dominate, making machine scheduling the critical constraint. Conversely, a high ratio indicated that transportation time dominates, shifting the bottleneck of JSP-AGV to AGV scheduling. The AGV quantity is the second influencing factor, as it directly affects whether sufficient AGV are available to the transport jobs to machine without delays. Meanwhile, the AGV battery capacity is a necessary but different type of constraint. It does not alter the JSP-AGV bottleneck but determines AGV availability by the frequency and duration of charging detours, which primarily impacts the charging frequency metric. This analysis clarifies that while battery capacity dictates charging logistics, the R_{tp} ratio and AGV quantity govern the core temporal dynamics and bottleneck behavior of JSP-AGV. The need for the AGV to charge station will change path planning in future research.

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