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Study on an autonomous distribution system for smart parks based on parallel system theory against the background of Industry 5.0

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ABSTRACT

The autonomous distribution systems used in smart parks against the background of Industry 5.0 require not only the consideration of the single goal of the economic benefits of enterprises, but also the fulfillment of their social responsibilities. Consequently, the scheduling of autonomous distribution systems and the trajectory planning of intelligent logistics vehicles have become increasingly more complex. Although technologies such as swarm intelligence have gradually been applied to the solution of independent distribution systems, there remain challenges in how to ensure that the production enterprises bear their responsibility to the public and consumers. Parallel system theory provides theoretical support for the concrete embodiment of people-oriented values in the smart park environment. In this work, based on parallel system theory, a parallel autonomous driving system is established. The system is mainly used for the autonomous transportation of finished products and materials in smart parks. The goal is to enhance the flexibility and efficiency of the distribution system in the park, and to highlight the people-oriented goal. Based on swarm intelligence theory and the A* algorithm, an improved swarm search optimization algorithm called IGSO-A* is developed to support the scheduling of parallel distribution systems and the trajectory planning of intelligent logistics vehicles. In two types of simulation experiments, compared with three other cutting-edge algorithms, the performance of the designed IGSO algorithm is improved by 4.6% on average. Moreover, compared with the A* algorithm, the performance of the proposed IGSO-A* algorithm is improved by 11.49%. The results prove the effectiveness of the proposed parallel autonomous distribution system in the distribution of finished products and materials in smart parks.

1. Introduction

As a new concept launched by the European Union in 2021, Industry 5.0 has been widely discussed by relevant researchers (Breque et al., 2021). It is a consensus of researchers that, in the context of Industry 5.0, society and the manufacturing industry are more sustainable, people-oriented, and flexible (Ahmed et al., 2022; Xu et al., 2021). At this stage, some research efforts are also devoted to the reduction of the environmental impact of industry (Hartel and Ghosh, 2022; Li et al., 2022; Sherazi et al., 2021), which provides some reference for the establishment of a sustainability model of the manufacturing industry. As a typical solution of Manufacturing 4.0, smart parks will continue to play an important role in the era of Industry 5.0. Different from the efforts made by smart parks to improve production economic benefits at this stage, the impact of production processes on the ecological environment and society will be more strongly considered for smart parks in the context of Industry 5.0 (Breque et al., 2021). However, it is worth noting that the people-oriented goal of the manufacturing industry has not been well-reflected. Therefore, it is necessary to focus on the construction of sustainable and people-oriented smart parks, especially the autonomous distribution system of smart parks, in the context of Industry 5.0. If enterprises wish to reflect the people-oriented enterprise value in the factory or industrial park environment of the manufacturing industry, they must determine the specific embodiment of people-oriented values in factory or industrial park scenes.

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The embodiment of people-oriented values in enterprise management is to ensure that employees have higher welfare, a better working environment, more dignity, etc. (de Souza João-Roland and Granados, 2023). However, it is evident that in the specific scenes of factories or industrial parks, this is just the basic "bottom line" of people-oriented values. Therefore, this study focuses on the specific embodiment of people-oriented values in the environment of factories or industrial parks, and preliminarily determines that the people-oriented values and sustainability of smart parks must not only protect the welfare, power, and dignity of enterprise employees in the parks; it is more necessary to improve the production efficiency and timeliness of distribution. The goal is for manufacturing enterprises to better fulfill their social responsibilities and to be responsible for people in society, thus ultimately better reflecting people-oriented values, rather than taking economic benefits as a single goal.

1.1. Motivation and contribution

At this stage, the relevant solutions of the independent distribution system in smart parks are aimed at maximizing the interests of the production enterprises, and ignore the impacts of the emissions and production efficiency of the distribution system in smart parks on consumers and the public; this is contrary to the industry requirements of Industry 5.0. Determining how to quantify the impact of smart parks on the environment and society is a major challenge when considering how to make the production enterprises in the parks better perform their social responsibilities. In addition, the social responsibility of production enterprises is considered in the independent distribution system, which increases the complexity of the problem and directly leads to the difficulty of solving it. In view of the problems existing in the scheduling of autonomous distribution systems and the track planning of intelligent logistics vehicles, based on parallel system theory, the social responsibility of the manufacturing enterprises in smart parks is introduced into the parallel autonomous driving system. A two-level mathematical model is established, and a digital twin model of non-person flow vehicles is designed. Furthermore, the IGSO and IGSO-A* algorithms are developed to improve the accuracy of solving the problem. Specifically, this work focuses on the autonomous distribution system of finished products and materials in smart parks to improve their production efficiency and increase their flexibility. The main contributions of this research are summarized as follows:

(1) This study discusses the specific embodiment of the people-oriented value goal in the smart park environment. Increasing the efficiency of the distribution of finished products and materials in the park is the key to improving the production efficiency of production enterprises, and is also the core content of the production enterprises to fulfill their social responsibilities.
(2) A parallel autonomous driving system for the distribution of finished products and materials in a smart park is established, and a two-level mathematical model for the path planning of unmanned logistics vehicles (ULVs) is developed. The first layer aims to plan the distribution sequence according to the materials sought by different stations in the park, and the second layer mainly plans the driving path of ULVs.
(3) To overcome the long search time of the A* and Group Search Optimizer algorithms when solving the problem of ULV routing, many strategies, such as follower selection, are introduced to improve the GSO algorithm. On this basis, the improved GSO (IGSO) algorithm is proposed to solve the problem.
(4) Finally, the results of a simulation experiment prove that the proposed IGSO and IGSO-A* algorithms are effective in dealing with the autonomous distribution of ULVs as compared with other algorithms. The findings provide theoretical support for the construction of intelligent parks with fully autonomous computing against the background of Industry 5.0.

The remainder of this paper is structured as follows. In Section 2, the research work related to Industry 5.0 and autonomous vehicle route planning is reviewed. Section 3 establishes a parallel system, and a new algorithm is designed in Section 4. Section 5 reports the simulation experiments. Finally, Section 6 summarizes the full text and discusses future research directions.

2. Related work

2.1. Industry 5.0

The proposition of Industry 5.0 provides a basis for the future development of industry and intelligent industrial equipment. Based on this, (Sharma and Arya, 2022) studied the application of unmanned aerial vehicles (UAVs) to the air quality detection of landfills against the background of Industry 5.0. (Yao et al., 2022) proposed a social-cyber-physical system (SCPS) paradigm based on the cyber-physical system (CPS). (Yin and Yu, 2022) focused on the green manufacturing of the manufacturing industry to highlight the green innovation of Industry 5.0. (Wang et al., 2023) also conducted research based on manufacturing in Industry 5.0. Different from (Yin and Yu, 2022), they mainly discussed the safety management of the manufacturing industry to highlight the people-oriented goal of Industry 5.0. (Hein-Pensel et al., 2023) also studied the value of being people-oriented in the context of Industry 5.0, but, different from the safety management of the manufacturing industry, they focused on the application of the refined model in the Industry 5.0 evaluation of small and medium-sized enterprises. (Qahtan et al., 2022) carried out research on sustainable transportation in the Industry 5.0 context. While their research on Industry 5.0 was more specific, they did not study a people-oriented transportation system in Transportation 5.0 (Qahtan et al., 2022). Furthermore, (Nayeri et al., 2023) studied supply chain planning in the era of the fifth industrial revolution and defined the main dimensions of Supply Chain 5.0 ().

2.2. Autonomous vehicle trajectory planning

AutoX's ULVs have been used in corresponding smart parks, and provided a hardware basis for the present research. At this stage, with the maturity of autonomous driving technology, a large number of unmanned vehicles and research on autonomous robot path planning have emerged (Guo et al., 2022; Li and Li, 2022). (Gu et al., 2022) studied the turning trajectory planning of autonomous mining vehicles. Similarly, (Tian et al., 2021) conducted research based on the trajectory planning problem of autonomous mining vehicles and established a multi-objective mathematical model for optimization. Liu et al. (Liu et al., 2017) considered constraints such as the turning angle of the vehicle body, and studied the turning path planning of autonomous vehicles while parking. (Wang et al., 2020) focused on a vehicle path planning method for autonomous vehicles at intersections, and essentially studied the vehicle turning problem. It is evident from the preceding literature review that, at this stage, relevant researchers have conducted in-depth research on the details of autonomous driving vehicle trajectory planning, such as vehicle turning, vehicle overtaking, and other issues; however, there is a lack of research on the global path planning of autonomous driving vehicles.

The research on the trajectory planning of autonomous robots, such as unmanned vehicles, unmanned ships, and UAVs, focuses on global path planning. (Zhou et al., 2021) solved the problem of global path planning for unmanned vehicles based on an artificial fish swarm algorithm. (Letizia et al., 2021) developed a recursive smooth trajectory generation algorithm to generate the global path of an unmanned vehicle. The research by (Josef and Degani, 2020) was based on the reinforcement learning method to study the vehicle path planning problem in environments with complex obstacles, which has a certain reference significance. The development of swarm intelligence technology provides a potential research direction for the global path planning of ULVs in the smart park environment.

3. System model

3.1. Parallel autonomous driving system

The specific embodiment of people-oriented values in the factory or industrial park environment is that production enterprises in the smart park earnestly fulfill their social responsibilities under the condition of ensuring the health and welfare of employees. To put it simply, the responsibility of production enterprises to society is to be responsible for all people in society, including the public, consumers, and employees. The determination of how to establish a CPS system to ensure the health and well-being of employees in the factory has been fully discussed in the extant literature (Adel, 2022; Leng et al., 2022). Thus, the present work focuses on the responsibility of manufacturers to the public and consumers. Specifically, the following two points are summarized.

(1) Manufacturers must be responsible for consumers who buy products. Thus, the flexibility of the production process, the faster production and transport of products, and the delivery of products to consumers within the expected time window must be ensured.
(2) Production enterprises must be responsible for the living environment of the public, including via the use of clean energy, to make the production process less energy-consuming and more sustainable.

These two points place higher requirements on the production and distribution of production enterprises. Due to space constraints, this study only discusses how the production links of enterprises are responsible for society. First, production enterprises should make the whole production process more unmanned to ensure that it is more flexible. In addition, production enterprises should optimize the production process to increase the collaboration of the work between each station. This places higher requirements on the unmanned transportation of materials and finished products between stations in smart parks, the key to which is the autonomous driving trajectory planning system of ULVs.

Both the human-cyber-physical system (HCPS) technology used by (Leng et al., 2022) and the cyber-physical cohesive systems (CPCS) mentioned by (Adel, 2022) protect the welfare of employees in the factory to achieve the goal of employee orientation. These two technologies do not have the universality of people-oriented values. It is worth noting that the cyber-physical-social systems (CPSS) and parallel system theory used by (Wang, 2010) and (Liu et al., 2022) consider the impact of the whole system on society. Therefore, parallel system theory pays more attention to the positive impact of the whole system on all people in society. In view of this advantage, reference is made to the strategic roadmap of Industry 5.0 formulated by (Ghobakhloo et al., 2022), and combines the digital twin technology (Li et al., 2023; Liu et al., 2023a, 2023b, 2023c, Zheng, 2023a, 2023b) to establish a parallel autonomous driving system of ULVs in a smart park. The specific architecture is shown in Fig. 1.

The parallel autonomous driving system presented in Fig. 1 is mainly composed of three parts, namely a physical system, a social system, and an artificial system. The automatic generator (including the scene generator, model generator, and algorithm generator) is responsible for inputting the contents of the social and physical systems into the artificial system in digital form. Specifically, the scene generator generates scene information according to the buildings in the smart park. The model generator generates a digital twin model according to the vehicle specification information. The algorithm generator calls algorithms in the algorithm library to solve the problem and to ultimately select the best algorithm to download on the ULV.

3.2. Double-layer mathematical model

To meet the requirements of the unmanned transportation of materials and finished products between stations in a smart park, as well as the requirements of human society for the autonomous driving trajectory planning of ULVs, a multi-objective and double-layer mathematical model is established. The model reduces the energy consumption of ULVs in the driving process and improves the vehicle operating efficiency, while also meeting the soft and hard time window constraints of each station on the arrival time. The purpose of improving the distribution efficiency is to reduce the waiting time of manufacturing workshops, increase the coordination of various manufacturing workshops, improve the production efficiency, and make the production process responsible for consumers. From the sustainability perspective, to reduce energy consumption is to reduce greenhouse gas emissions, and to ultimately be responsible for the living environment of the public.

Fig. 2 presents the schematic diagram of autonomous driving trajectory planning for ULVs. The different stations in the smart park are mainly divided into manufacturing workshops, warehouses, and parking lots. A park with six stations is considered in this work. Stations 2, 3, and 4 are the manufacturing workshops, and the order of warehousing is 2 → 3 → 4. Station 5 serves as a temporary warehouse to store materials, semi-finished products, and finished products. Station 6 is the finished product warehouse. The topological relationship between stations is shown in Fig. 3, and Table 1 defines some parameters used in this article.

The first-level model is similar to the vehicle routing problem (VRP). The soft and hard time window constraints of the station, the speed constraints of the vehicle, and other constraints are considered. With the shortest path as the goal, the distribution sequence of ULVs is planned by constructing the distance matrix between stations. The specific model is as follows.

$$\min f_1 = \sum_{s_i = S} \left(l_{ij} \times \psi_{um,ij} \right) \tag{1}$$

$$\psi_{u_m,ij} \in \{0,1\}, \forall u_m \in U \tag{2}$$

$$\begin{cases} \forall s_i \in S, l_{62} \notin L \\ \forall s_i \in S, l_{63} \notin L \\ \forall s_i \in S, l_{64} \notin L \\ \forall s_i \in S, l_{65} \notin L \end{cases} \tag{3}$$

$$\sum_{\forall s_i \in S} \left(w_{Ini} \times \psi_{um,ij} \right) \leqslant W_{u\max} \tag{4}$$

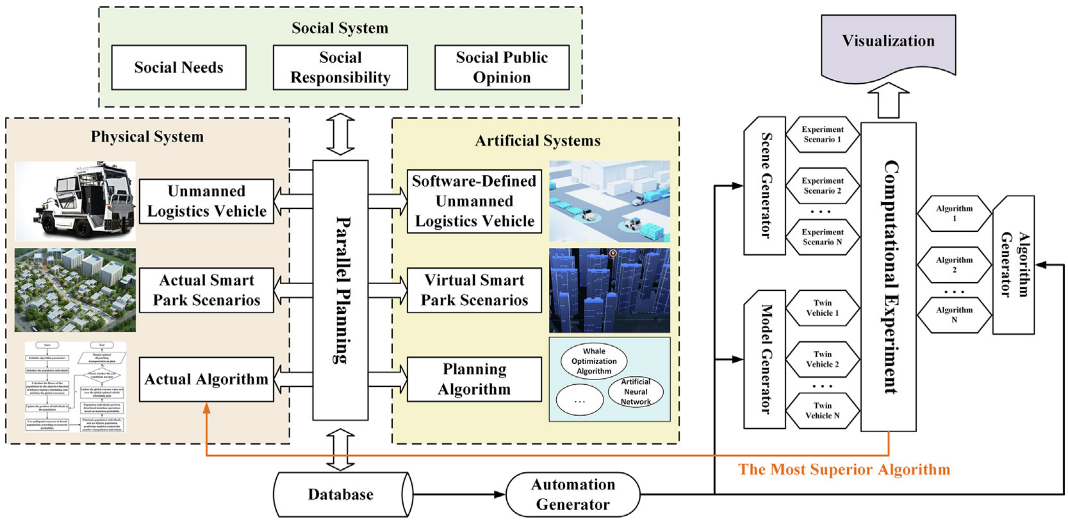

Fig. 1. The framework of a parallel autonomous driving system of ULVs for smart parks.

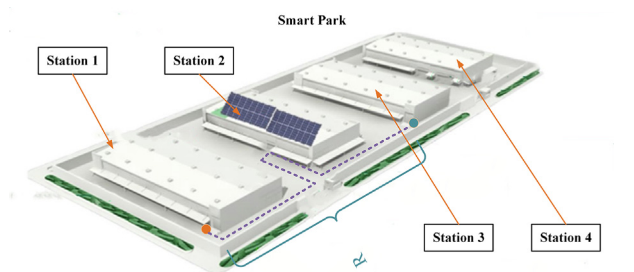

Fig. 2. The schematic diagram of autonomous driving path planning for ULVs.

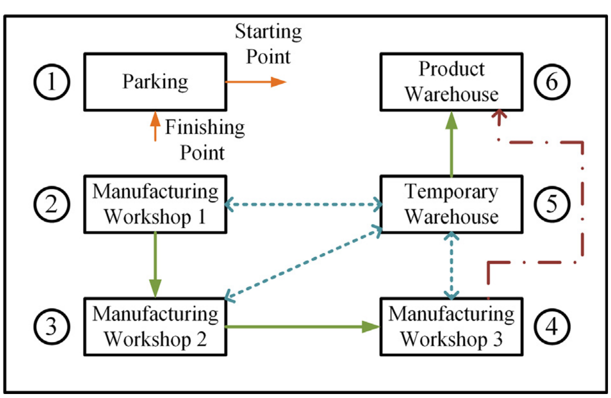

Fig. 3. The topological relationships between stations in the smart park.

$$\sum_{\forall u_m \in U} \psi_{u_m,ij} \leqslant N_{u\max} \tag{5}$$

$$\sum_{\forall s_j \in S} \frac{(l_{jj'} \times \psi_{um,jj'})}{\bar{v}} \leqslant \min\{T_{Oui}, T_{Ini}\}, \forall s_i \in S \tag{6}$$

Eq. (1) is an objective function that minimizes the global path of ULVs. The result of Eq. (2) is a 0–1 variable. When ULV u_m travels from station s_i to station s_j, $\psi_{u_m,ij}$ is 1; otherwise, $\psi_{u_m,ij}$ is 0. Eq. (3) reflects the topological relationships between stations in the smart park. Eq. (4) is the maximum load constraint of ULVs, and Eq. (5) is the maximum number constraint of ULVs. Finally, Eq. (6) is the time window constraint of the station on the arrival time of ULVs.

Table 1
The definitions of parameters.

Parameter	Definition
S	Set of stations, $S = \{s_0, s_1, s_2, \cdots, s_n\}$, where s_0 is the parking lot
U	Set of ULVs, $U = \{u_1, u_2, \cdots, u_m\}$
L	$\forall l_{ij} \in L$, where l_{ij} is the distance between stations s_i and s_j
$\bar{v}$	Average speed of ULVs
w_{Oui}	Weight of materials/finished products for ex-warehouse operation at station s_i
w_{Ini}	Weight of materials/finished products for in-warehouse operation at station s_i
$N_{u\max}$	Maximum number of ULVs
$W_{u\max}$	Maximum load of ULVs
K	Set of trajectory points of ULVs, $K = \{1, 2, 3, \cdots, k\}$
R	Set of path segments included in the trajectory of ULVs, $R = \{r_{1,2}, r_{2,3}, \cdots, r_{p,q}\}, \forall p, q \in K$
$\overrightarrow{p'p}$	Track segment vector of a ULV from node p' to node p, where $\overrightarrow{p'p} = (x_p, y_p, z_p)$
$\beta_{p,q}$	Slope of path segment $r_{p,q}$
T_{Oui}	Latest time of departure from station s_i
T_{Ini}	Latest time of warehousing in station s_i

The second-level mathematical model considers the kinematic constraints of the ULV, including the body turning angle, front wheel turning angle, vehicle length and width, etc. The specific schematic diagram is shown in Fig. 4. Furthermore, a multi-objective function is established to minimize the energy consumption and distribution time of the planned track. The details are as follows.

$$\min f_2 = \sum_{\forall p,q \in K} \frac{r_{p,q}}{\bar{v}} \times \sum_{\forall p,q \in K} E_{p,q} \tag{7}$$

$$F_{p,q} = \begin{cases} \sin(\beta_{p,q}) \times G_u + \rho \times A \times C_d \times \left(\vec{v} + \vec{v}_{wind}\right)^2 + C_r \times \cos(\beta_{p,q}) \times G_u, z_p \geqslant 0 \\ \rho \times A \times C_d \times \left(\vec{v} + \vec{v}_{wind}\right)^2 + C_r \times \cos(\beta_{p,q}) \times G_u - \sin(\beta_{p,q}) \times G_u, z_p < 0 \end{cases} \tag{8}$$

$$E_{p,q} = F_{p,q} \times r_{pq} \tag{9}$$

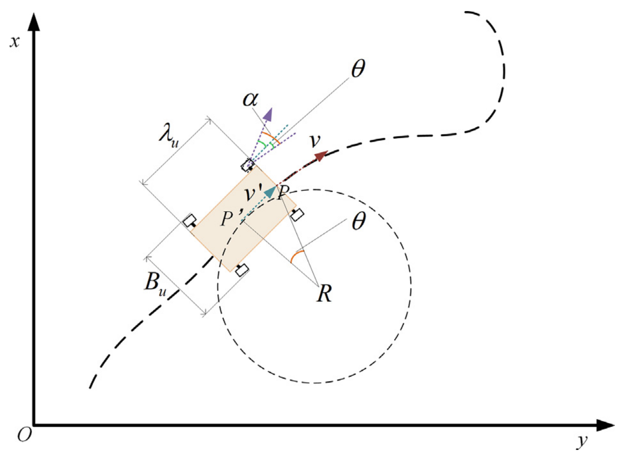

Fig. 4. The kinematic constraint diagram of the ULV.

$$\cos\left(\theta_p\right) = \frac{\overrightarrow{p''p'} \cdot \overrightarrow{p'p}}{\left|\overrightarrow{p''p'}\right| \cdot \left|\overrightarrow{p'p}\right|}, \forall p', p, p'' \in K \tag{10}$$

$$\theta_{\min} \leqslant \theta_p \leqslant \theta_{\max}, \forall p \in K \tag{11}$$

$$\alpha_p = \begin{cases} \theta_{p-1} + \theta_p, 0 \leqslant \theta_p \leqslant \frac{\pi}{2} \\ \theta_p - \theta_{p-1}, \frac{\pi}{2} \leqslant \theta_p \leqslant \pi \end{cases} \tag{12}$$

$$\alpha_{\min} \leqslant \alpha_p \leqslant \alpha_{\max}, \forall p \in K \tag{13}$$

Eq. (7) is the objective function of the second-level mathematical model, and $E_{p,q}$ is the energy consumption of ULVs in route section $r_{p,q}$. Eq. (8) describes the force on the ULV at route section $r_{p,q}$, where C_d and C_r are respectively the air resistance coefficient and road friction resistance coefficient of the ULV. Moreover, G_u is the gravity of the ULV, ρ is the air density, A is the cross-sectional area of the ULV, $\overrightarrow{v}$ is the speed of the ULV, and $\overrightarrow{v}_{wind}$ is the wind speed. Eq. (9) is the calculation method of energy consumption. Eqs. (10) and (11) are the body turning angle constraints of the ULV, where θ_p is the body turning angle of the ULV at point p, and $\theta_{\max}$ and $\theta_{\min}$ are respectively the maximum and minimum turning angles of the body of the ULV. Eqs. (12) and (13) are the front wheel turning angle limit of the ULV, where α_p is the front wheel turning angle of the ULV at point p, and $\alpha_{\min}$ and $\alpha_{\max}$ are respectively the maximum and minimum turning angles of the front wheel of the ULV.

4. Algorithm design

To provide the algorithm library in the parallel autonomous driving system with more high-performance algorithms, a new algorithm is designed. In view of the low convergence accuracy of the GSO algorithm when dealing with optimization problems with high complexity, as well as its ease of falling into local optimal solutions (Liu et al., 2022), the algorithm is improved according to the search strategies of the artificial bee colony (ABC) algorithm (Rambabu et al., 2022) and the sparrow search algorithm (SSA) (Kathiroli and Selvadurai, 2022). The IGSO algorithm is ultimately developed to solve the first-level model. On this basis, in view of the shortcomings of the A* algorithm in dealing with the vehicle trajectory planning problem in three-dimensional (3D) space, such as unsatisfactory results and redundant trajectories, the IGSO algorithm is introduced to the trajectory planning problem of ULVs according to the search framework of the A* algorithm to solve the problem.

4.1. Algorithm introduction

As a novel heuristic algorithm, the GSO algorithm has been widely used in optimization problems (Liu et al., 2022). The algorithm was inspired by the foraging behavior of social animals, according to which the individuals in the whole population are divided into discoverers, joiners (also called followers), and wanderers. A discoverer is an individual who finds food, and the fitness function value of the discoverer is optimal. During the search process, the discoverer searches around itself. When the discoverer finds food, the discoverer has a certain attraction to other individuals, and the joiner is attracted by it and searches in the direction of the discoverer. Wanderers are not affected by the attractiveness of the discoverer and search in their own direction. The existence of wanderers is the key for the GSO algorithm to jump out of the local optimal solution.

The ABC algorithm was designed by Karaboga et al. (Kathiroli and Selvadurai, 2022) to solve multivariable optimization problems. Inspired by the honey-gathering behavior of bees, it has the advantages of a simple structure and few parameters. In the process of algorithm optimization, the whole artificial bee colony is divided into three kinds of individual bees, namely leading bees (also known as hiring individual bees), following bees, and detecting bees. Among them, leader have the solution vector in the problem solution space, and search near the solution vector in the iterative process. Leader attract a certain number of following bees according to the fitness function value corresponding to their solution vector; if the following bee does not find a solution vector with a better fitness function value during multiple iterations, it will turn to the reconnaissance peak to search the solution space.

Different from the GSO algorithm, the role conversion among the three individual bees in the ABC algorithm has certain regularity; the role conversion among the three individuals in the GSO algorithm is more random. The SSA is similar to the GSO and ABC algorithms, and is generated by imitating the feeding behavior of sparrows. The whole sparrow population is divided into three kinds of individuals, namely finders, joiners, and watchers. However, different from these algorithms, the SSA includes the addition of a sparrow to avoid the strategy of hunters, which greatly increases the ability of the algorithm to jump out of the local optimal solution.

4.2. IGSO algorithm

Step 1. Initialize the dimensions of the problem D, including the number of individuals H, the maximum number of iterations $\lambda_{\max}$, the Euclidean distance between the upper and lower bounds of the solution space $\chi_{\max}$, the maximum steering angle $\delta_{\max}$, and the maximum evaluation algebra $\xi_{\max}$.

Step 2. Calculate the angle and direction of the head of the individual in the solution space.

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^D \\ x_2^1 & x_2^2 & \cdots & x_2^D \\ \vdots & \vdots & \vdots & \vdots \\ x_H^1 & x_H^2 & \cdots & x_H^D \end{bmatrix} \tag{14}$$

$$\delta = \begin{bmatrix} \delta_1^1 & \delta_1^2 & \cdots & \delta_1^{D-1} \\ \delta_2^1 & \delta_2^2 & \cdots & \delta_2^{D-1} \\ \vdots & \vdots & \vdots & \vdots \\ \delta_H^1 & \delta_H^2 & \cdots & \delta_H^{D-1} \end{bmatrix} \tag{15}$$

$$B = \begin{bmatrix} B_1^1 & B_1^2 & \cdots & B_1^D \\ B_2^1 & B_2^2 & \cdots & B_2^D \\ \vdots & \vdots & \vdots & \vdots \\ B_H^1 & B_H^2 & \cdots & B_H^D \end{bmatrix} \quad (16)$$

Eq. (14) is the position of each individual in the solution space, the dimension of which is D. Eq. (15) is the head angle of each individual, the dimension of which is D-1. Eq. (16) is the forward direction of each individual in the solution space, the dimension of which is D. The forward direction is calculated from the head angle, and the specific calculation method can be found in the publication by (Liu et al., 2022).

Step 3. Divide the roles of individuals according to their positions.

Step 4. Execute the finder search strategy. As the individual with the best fitness function value in the population, the discoverer searches near its own solution vector. The specific formula is as follows:

$$X_{p*} = \begin{cases} X_p + r_1 \times \chi_{\max} \times B_p(\delta) \\ X_p + r_1 \times \chi_{\max} \times B_p\left(\delta + r_2 \times \frac{\delta_{\max}}{2}\right) \\ X_p + r_1 \times \chi_{\max} \times B_p\left(\delta - r_2 \times \frac{\delta_{\max}}{2}\right) \end{cases} \quad (17)$$

where X_p is the current position vector of the discoverer, X_{p*} is the position vector of the discoverer in the next generation, r_1 is a random number conforming to the standard normal distribution, and r_2 is a random number within the interval (0,1). In the three vectors of X_{p*}, if $\exists fit(X_{p*}) \leqslant fit(X_p)$, X_p moves to the best position $\min\{X_{p*}\}$ among the three positions; otherwise, it will not move, but will only turn its head. The specific formula is given by Eq. (18). $fit(X_p)$ is the fitness function value of solution vector X_p.

$$\delta^{\lambda+1} = \delta^{\lambda} + r_2 \times \frac{\delta_{\max}}{2} \quad (18)$$

After the maximum evaluation algebra $\xi_{\max}$, the current position of the discoverer is evaluated. If the discoverer does not find a better position after the iteration of generation $\xi_{\max}$, the head angle is restored to that before generation $\xi_{\max}$, as given by Eq. (19).

$$\delta^{\lambda+\xi_{\max}} = \delta^{\lambda} \quad (19)$$

Step 5. The followers choose strategies. Some individuals in the group become followers according to a certain probability, thus allowing for updating according to the behavior of followers. Referring to the formula of the probability of observer bees choosing to follow other individuals in the ABC algorithm, a follower selection strategy is designed:

$$P_i = \frac{fit\left(X_i^{\lambda}\right)}{fit\left(X_p^{\lambda}\right)} \quad (20)$$

$$X_i^{\lambda+1} = X_i^{\lambda} + r_3\left(X_p^{\lambda} - X_i^{\lambda}\right) \quad (21)$$

where P_i is the probability of the individual becoming a follower in the solution space, r_3 is a random number generated in the interval (0,1), X_p^{λ} is the solution vector of the optimal fitness function value generated in the iteration process of generation λ, and X_i^{λ} is the solution vector of individual i in the iteration process of generation λ.

Step 6. Execute the wanderer location update strategy. Individuals in the population become wanderers with $1 - P_i$ probability. Referring to the location update strategy of the discoverer in the SSA, the wandering search strategy in the GSO algorithm is improved, as given by Eq. (22):

$$X_i^{\lambda+1} = \begin{cases} X_i^{\lambda} + \xi_{\max} \times r_1 \times \chi_{\max} \times B_p\left(\delta^{\lambda+1}\right), r_1 \leqslant r_4 \\ X_i^{\lambda} \times \exp\left(-\frac{i}{\xi_{\max}}\right), r_1 > r_4 \end{cases} \quad (22)$$

where r_4 is a random number in the interval [0.5,1].

Step 7. Judge whether the maximum number of iterations is reached. If the maximum number of iterations is reached, end the cycle and output the results; if not, return to Step 3 to continue the cycle.

In the process of ULV trajectory planning, the IGSO-A* algorithm is developed by using the path search method of the A* algorithm as a reference, namely that it can move in eight directions. This minimizes the objective function value of the second-level model, thus completing the trajectory optimization process.

5. Simulation experiments

To verify the effectiveness of the established parallel system, a 3D environment model of the smart park was established and verified via a simulation example. The simulation experiments were conducted with MATLAB R2017a with Windows 10 as the operating system, 16G of computer memory, and Intel i7-8750H as the CPU. The details are as follows: dimension of the problem $D = 33$; number of individuals $H = 50$; maximum number of iter-

Table 2
The outbound and inbound requirements of each station in the smart park.

Station	Outbound demand(unit: tons)	Inbound demand(unit: tons)
1	0.0	0.0
2	0.3	0.1
3	0.0	0.4
4	0.2	0.1
5	0.6	0.0
6	0.0	0.5

Table 3
The optimal results of the four algorithms during 20 runs.

Algorithm	Route	Path length (unit: meters)	Driving time (unit: seconds)
GSO	1-5-3-5-2-3-4-6	9537	1718
ABC	1-5-2-5-3-4-5-6	9309	1677
SSA	1-5-3-5-2-3-4-6	8924	1608
IGSO	1-5-2-3-4-5-6	8847	1594

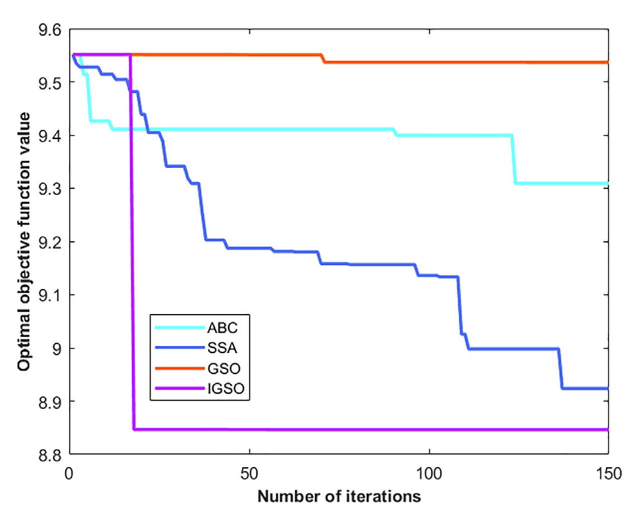

Fig. 5. The optimal iteration curves of the four algorithms during 20 runs.

ations $\lambda_{max} = 150$; Euclidean distance of the upper and lower bounds of the solution space $\chi_{max} = 5$; maximum steering angle $\delta_{max} = \pi/(\xi_{max})^2$; maximum evaluation algebra $\xi_{max} = 5$.

Table 2 lists the outbound and inbound requirements of each station in the smart park.

In the process of solving the first-level model, the GSO (Liu et al., 2022), ABS (Cui et al., 2023; Rambabu et al., 2022), and SSA (Kathiroli and Selvadurai, 2022; Zhang and Han, 2022), which are more advanced algorithms used in robot scheduling and planning, were selected for comparison with the designed IGSO algorithm. The minimum and maximum turning angles of the body of the ULV were respectively 20° and 120°, and the vehicle body width was 3 m. The minimum and maximum turning angles of the tire were respectively 10° and 140°. In the process of solving the first-level model, for the convenience of calculation, the global map is rasterized.

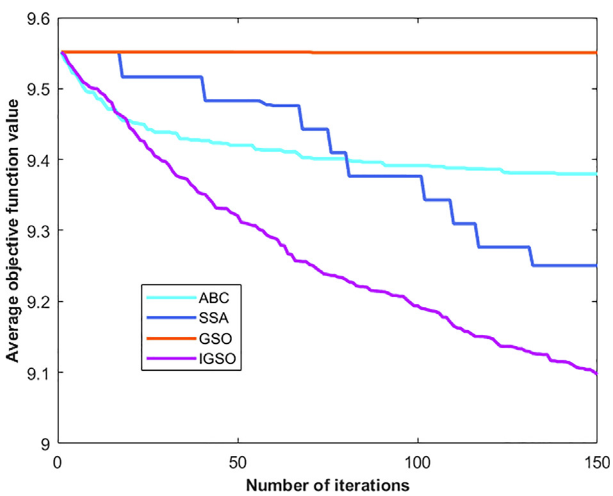

Fig. 6. The average iteration curves of the four algorithms during 20 runs.

Table 4
The optimal, worst, and average objective function values of the four algorithms during 20 runs when solving the first-level mathematical model.

Algorithm	Index		
	Optimal value	Worst value	Average value
GSO	9.537	9.552	9.551
ABC	9.309	9.550	9.380
SSA	8.924	9.438	9.251
IGSO	8.847	9.270	9.097

In the process of solving the first-level model, the four algorithms were respectively run 20 times. The best running result among the 20 running processes was selected. The specific routes and driving time are shown in Table 3, and the iteration curves are shown in Fig. 5. Further, Fig. 6 presents the average convergence curves of the four algorithms during the 20 runs. The average values, the worst values, and the best values of the objective functions during the 20 runs of the four algorithms when solving the first-level mathematical model are reported in Table 4.

It can be seen from Table 3 that the ULV scheduling problem in the smart park is different from the general VRP. The ULVs can return to the warehouse from any point to pick up materials and then distribute them again. From the path length reported in Table 3 and the convergence curve presented in Fig. 5, it can be seen that the IGSO algorithm achieved higher convergence accuracy and a stronger ability to jump out of the local extremum in dealing with ULV scheduling problems as compared with the other three algorithms. The data exhibited in Fig. 6 and Table 4 prove that the IGSO algorithm is more robust than the other three algorithms.

In the planning process of the second-level mathematical model, based on the results of the first-level model planning the arrival sequence between stations, the distribution scheme planned by the IGSO algorithm was selected for use in the IGSO-A* algorithm to further plan the 3D trajectory of ULVs. The A* algorithm used by (Lian et al., 2021) was selected for comparison with the proposed IGSO-A* algorithm. The 2D and 3D views of the ULV trajectories planned by the IGSO-A* algorithm are respectively shown in Fig. 7 (a) and (b). The 2D and 3D views of the ULV trajectories planned by the A* algorithm are respectively shown in Fig. 8 (a) and (b). The various indicators of the 3D trajectory planned by IGSO-A * and A * algorithms when solving the second-level mathematical model are shown in Table 5.

From Figs. 7 and 8, it can be seen that the A* algorithm generated a large number of redundant tracks as compared with the IGSO-A* algorithm when planning the trajectories of ULVs. It can be seen from Table 5 that the track length of the IGSO-A* algorithm was 9064.07 m, and that of the A* algorithm was 9670.79 m. According to the planning results, the energy consumption of the trajectory planned by the A* algorithm was 11.49% greater than that of the IGSO-A* algorithm, and the travel time of the trajectory planned by A* algorithm was 6.68% greater than that of the IGSO-A* algorithm. Therefore, it can be concluded that the proposed IGSO-A* algorithm is superior to the A* algorithm in solving the 3D trajectory of ULVs.

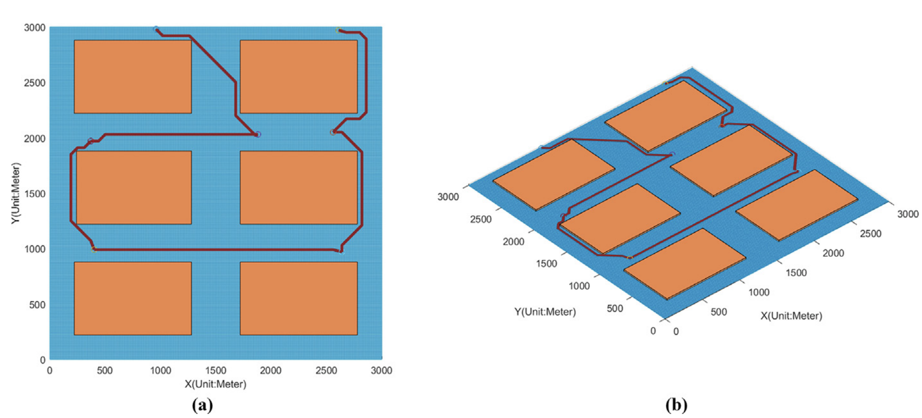

Fig. 7. The track of a ULV planned by the IGSO-A* algorithm.

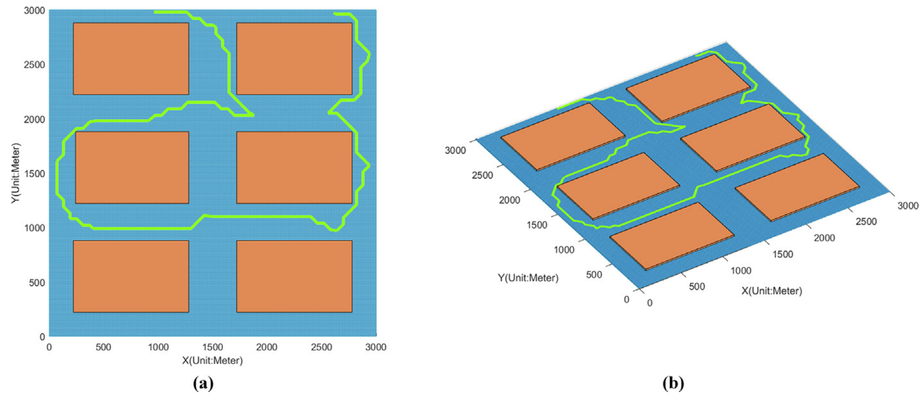

Fig. 8. The track of a ULV planned by the A* algorithm.

Table 5
The comparison results of various indicators between A * and IGSO-A * algorithms when solving the second-level mathematical model.

Algorithm	Path length(unit: meters)	Driving time(unit: seconds)	Energy consumption (unit: kw·h)
IGSO-A*	9064.07	1633.17	1.95
A*	9670.79	1742.48	2.17

6. Conclusion

In response to the requirements of Industry 5.0 for autonomous distribution systems in smart parks, parallel autonomous driving systems for material distribution in smart parks were researched in this study. For a parallel autonomous driving system based on parallel system theory, a high-precision digital twin model of ULVs was developed based on the physical performance constraints of real ULVs. In addition, a two-layer mathematical model for autonomous material distribution in smart parks was designed with the goal of ensuring the productivity of enterprises and making their production processes more energy-efficient and sustainable. Furthermore, to improve the solution accuracy of the algorithms in the algorithm library of the parallel automated driving system when solving complex optimization problems, the IGSO and IGSO-A* algorithms were proposed. The results of simulations demonstrated that, during 20 runs, the average fitness function value of the IGSO algorithm was reduced by 1.69–4.55%, and the optimal fitness function value was reduced by 0.87–7.80%, as compared with the scheduling solutions of ULVs solved by the GSO, ABS, and SSA algorithms. The worst fitness function value of the IGSO algorithm was reduced by values ranging from 1.69% to 3.07%. In the trajectory planning process of ULVs, the energy consumption of the trajectory planned by the A* algorithm was 11.49% greater than that of the IGSO-A* algorithm, and the travel time of the trajectory planned by the A* algorithm was 6.68% greater than that of the IGSO-A* algorithm. In future work, focus will be placed on the dynamic obstacle avoidance problem of ULVs to smoothly realize vehicle-human obstacle avoidance and increase the safety of the system.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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