IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 28, 2021, accepted May 4, 2021, date of publication May 6, 2021, date of current version May 13, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3077974

Research on Design of Cross-Aisles Shuttle-Based Storage/Retrieval System Based on Improved Particle Swarm Optimization

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ABSTRACT The cross-aisles shuttle-based storage/retrieval system has not only storage function but also the sorting function and makes full use of warehouse space to achieve high-density storage. It uses ''part-to-picker'' order picking mode to respond quickly to orders and shorten sorting time. In this paper, through the analysis of the system, an effective evaluation method for the efficiency and time of system picking under a single instruction operation cycle is presented. The objective function of system minimum cost under the condition of satisfying customer's demand is constructed. The objective function is solved by an improved particle swarm algorithm based on the optimized initial particle swarm optimization. By optimizing, we can find the optimal configuration of the system (i.e., the number of tiers, number of aisles and number of bays, number of picking stations, and number of lifts with minimal system cost). Finally, the impact of different configurations on system performance is summarized. This method can guide the design planner to design a more reasonable system under minimum cost control.

INDEX TERMS Shuttle-based storage/retrieval system, performance analysis, system design, part-to-picker, improved particle swarm optimization.

I. INTRODUCTION

A. BACKGROUND

With the rapid development of the e-commerce industry and the continuous innovation of automation technology, the ''Part-To-Picker'' order picking system has replaced the traditional ''Picker-To-Part'' picking model, widely favored by e-commerce companies [1]. ''Part-To-Picker'' order picking systems mainly include the following: automated storage and retrieval system (AS/RS), shuttle-based storage/retrieval system (SBS/RS), and an order sorting system based on mobile robots (Robotic mobile fulfillment systems, RMFS). AS/RS is the parallel work of stackers dedicated to each aisle to complete the storage and retrieval tasks of the system [2]. SBS/RS is an automatic shuttle that runs along the aisle and cooperates with a lift to complete the task of storage and retrieval across tiers. In SBS/RS, shuttles replace the pickers, receive orders from the picking station through a wireless network, and perform parallel operations to complete storage and sorting tasks.

The associate editor coordinating the review of this manuscript and approving it for publication was Derek Abbott.

The cross-aisles shuttle-based storage/retrieval system (CASBS/RS) takes the shuttle as the carrier and cooperates with the lift to perform tasks. It is also a kind of SBS/RS. Its large storage capacity, small footprint, high sorting efficiency, and fast response speed have received extensive attention from e-commerce companies. CASBS/RS is composed of multi-tier and multi-aisle three-dimensional racks, aisle shuttle, cross-aisle shuttle, lift, picking table, buffer area, and conveyor belt. Each piece of equipment works in parallel with each other, shortening the order picking time and improving the picking efficiency. The reloading shuttle can transport cargos in different aisles to the same picking station so that the system can pick-to-order across aisles and shorten the order picking time.

B. SYSTEM LAYOUT

The layout configuration of each level of CASBS/RS is shown in the Fig.1. In the CASBS/RS system, turnaround boxes are generally used as containers to place cargos on shelves to facilitate selection and realize dense cargos storage. As shown in Fig.1, each storage aisle has a row of shelves on both sides, a white square on each row of shelves is a storage

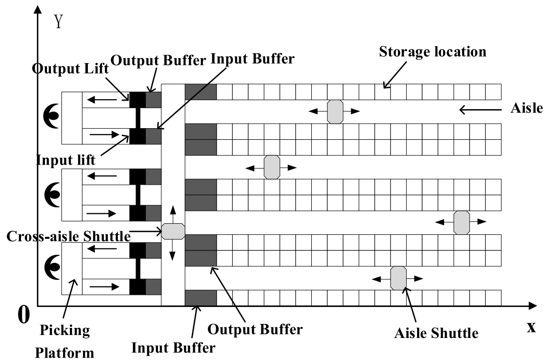


FIGURE 1. **The top view of the CASBS/RS system.**

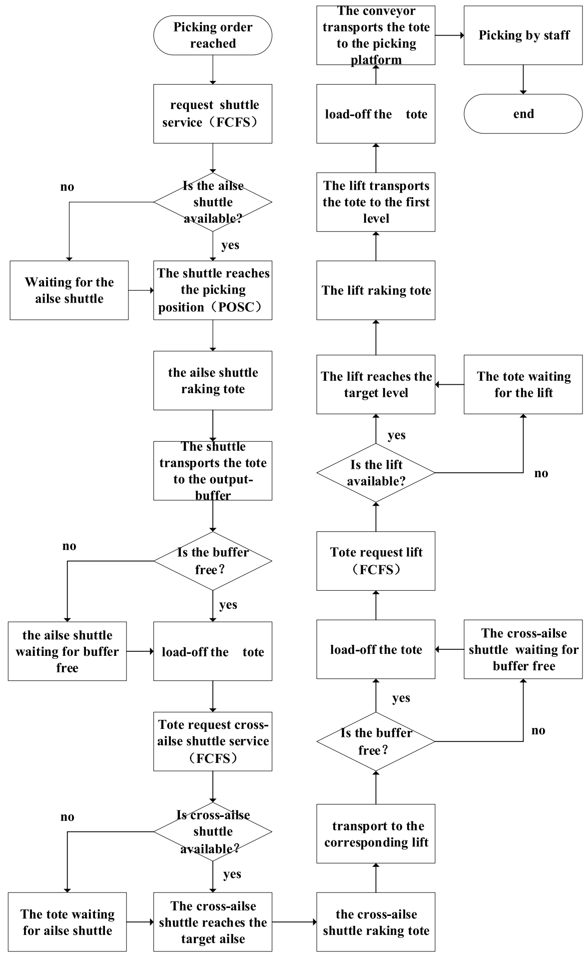


FIGURE 2. **The process of out-put delivery in CASBS/RS system.**

space, which can be placed in a turnaround box. Shuttle is responsible for the horizontal movement of cargos and lift is responsible for the vertical movement of cargos. Shuttle are further divided into aisle shuttle and cross-aisle shuttle.

There is an aisle shuttle responsible for horizontal movement of cargos in the X-direction on each tier of the three-dimensional rack. In the front section of the three-dimensional rack in each aisle, there is a group of high-speed lift (a high-speed lift for warehousing and a high-speed lift for warehousing) responsible for the vertical movement of cargos. Each group of high-speed lifts serves only one pick-up platform, relying on a conveyor to transport cargos between the pick-up platform and the lift. A major advantage of CASBS/RS system over traditional SBS/RS system is that in each level there is a cross-aisle shuttle responsible for horizontal movement of cargos in the Y direction so that cargos can be transported across aisles by the cross-aisle shuttle, greatly improving the flexibility of the system and the selection task can be directly selected on a single order. The grey area in Fig.1 is a buffer area, which is mainly divided into two parts, one part is between the warehouse lift and the cross-aisle shuttle, the other part is between the aisle shuttle and the cross-aisle shuttle. The main function is to temporarily store the tote, reduce the time taken up by the tote for shuttle and lift, improve the shuttle and shuttle operation efficiency, and improve throughput capacity.

C. WORKFLOW

Batch order is processed, the picking task generated by the WCS system is sent to CASBS/RS system. After the sorting task has been reached, first request the aisle shuttle of the aisle where the target cargos are located for service. If the aisle shuttle of the current aisle is performing other tasks, the sorting task will enter the waiting sequence and wait for the aisle shuttle service to be completed; If the aisle shuttle in this aisle is idle, this shuttle responds to the selection job and reaches the cargo position where the target cargo is located to pick up the cargo, then runs along the guide rail of the aisle and transports the tote of the target cargo to the output caching area. If the output caching area is full, the aisle shuttle car needs to enter the waiting state and wait for the output caching area to be idle.

If the outlet buffer is idle, the aisle shuttle unloads the cargo turnaround box and enters the idle state waiting for the arrival of a new selection task. The cargo turnaround boxes placed in the out-of-warehouse buffer area request the cross-aisle shuttle to be reloaded. In turn, the cross-aisle shuttle fulfills functions by the FCFS principle, and the shuttle requests the out-of-warehouse lift for service. If the out-of-warehouse lift is in an in-service state, then the turnaround box waits. If the warehouse lift is idle at this time, the cross-aisle shuttle will unload the cargo to the lift and continue to respond to the new task. After the warehouse lift receives the task request of the cargo tote, it will transport the tote to one level and unload it on the conveyor. The conveyor will transport the cargo tote to the corresponding picking table. Finally, the worker picks the cargos from the tote and completes the picking operation.

D. CONTRIBUTIONS

The main contributions of this paper are:

1) Present an effective evaluation method for the picking efficiency and picking a time of CASBS/RS.

2) Establish a multi-objective mathematical model for the minimum cost and the maximum throughput capacity of CASBS/RS.

3) Design an improved PSO algorithm and optimize the initial particles for solving the problem of the optimal configuration.

4) Summarize the impact of different configurations on the performance of the system. This research can guide the design planner to design a more reasonable system under minimum cost control.

II. LITERATURE REVIEW

Today, to meet customers' needs, the timeliness of picking order processing is increasingly important, so the operation efficiency of the automatic picking system is also increasing [3]. Enterprises adopt shuttle-based storage/retrieval systems with the advantages of large throughput, high flexibility, and high utilization rate [4].

Currently, the research on shuttle-based storage/retrieval systems mainly focuses on the system's performance analysis, system design and operation strategy. Queuing theory is generally used in the performance analysis of systems [5], [6]. By modeling the system as an integrated queuing network, the cycle time and resource utilization are estimated [7]. They model each tier as a semi-open queueing network and the vertical transfer unit as a multi-class queueing network. Besides, some scholars present an analytic travel time model and a calculation method for throughput performance of SBS/RS [8]–[10]. They develop a closed-form expression for the cycle time and consider the effect of shuttle acceleration and deceleration. But these studies are only for a tier-captive SBS/RS or tier to tier SBS/RS.

As for system design related problems, many researchers have devoted themselves to study how warehouse layout and device configuration influence system performance. Malmborg and his team first researched this system. They established an SBS/RS optimization model and optimized system performance by setting system configuration parameters [11]. On this basis, Malmborg adds the number of lifts in the system to the model and presents a state equation model to predict the system's ratio of the two instruction cycles. In addition to estimating the storage and retrieval cycle time, the ratio can also be used to estimate the utilization and throughput of the system [12]. Later, some scholars studied other types of systems. Zhang [13] and Cao [14] establish semi-open-loop queueing networks for tier to tier SBS/RS and four-way SBS/RS, respectively, and study the optimal configuration when the system reaches the maximum performance.

With regard to operation strategy of SBS/RS, research about order strategy, task scheduling strategy, and storage assignment etc. have been developed for a long time. Wang proposed a system optimization method that could select system applicability according to different order types and carried out applicability analysis of two types of "delivery to person" systems for different order types [15]. Wu put forward the order sorting optimization model and optimized the order sorting through the improved K-means clustering algorithm to improve the picking efficiency of the system [16]. Eder considers the classified storage strategy based on probability and studies the impact of different storage strategies on system performance [17], [18]. Liu establishes an energy consumption model for the shuttle robot system under dual-command operation, demonstrates that the acceleration and maximum speed of system equipment are the main factors affecting energy consumption, and analyses the relationship between throughput and energy consumption [19].

In terms of methods to solve SBS / RS related problems. A time sequence mathematical model based on the motion of the shuttles and stacker crane is proposed. An improved Pareto-optimal elitist non-dominated sorting genetic algorithm is used to solve the objectives of minimizing the total working time of the stacker crane and the wasted shuttle time [20]. Reference [21] proposes a hybrid algorithm based on the ant colony algorithm, and an adaptive extensive neighborhood search is submitted to solve the problem of system throughput. However, these studies did not consider the total cost of the system.

Based on previous research about SBS/RS, this study is mainly aimed at Cross-aisles Shuttle Based System/Retrieval System. An improved particle swarm algorithm is proposed to determine the best system design scheme to meet the needs of enterprises. And ensure the minimum total cost of the system.

III. PROBLEM DESCRIPTION

A. MAIN ASSUMPTIONS

The research is based on some assumptions which are in accordance with real situations in CASBS/RS. and the main assumptions are listed as follows:

1) Following the POSC (Point-Of-Service-Completion) principle, the shuttle and lift stop at the last task after it has completed the task.

2) Follow the FCFS (First-Come First-Served) principle that shuttles, lifts, and picking desks all serve the received requests on a first-come-first-service basis.

3) Random storage strategy, i.e. the probability that a picking order task hits a storage location is the same.

4) Only one cargo tote can be transported with the same picking task of lift and shuttle.

5) The arrival rate of the picking order follows a Poisson distribution with parameter lambda and the service time of each service equipment follows a general distribution.

6) No more than one turnaround box per service equipment.

B. MAIN NOTATIONS

To simplify the description of analytical models, we used the main notations in the remainder of the paper are listed as follows.

λ_r	Arrival rate of picking tasks (i.e., the number of tasks received by the system per hour per unit time)
n_A	Number of aisles in CASBS/RS
n_T	Number of tiers in CASBS/RS

n_C	Number of bays in CASBS/RS
n	Total number of storage locations in CASBS/RS
n_p	The number of lifts in the system is also the number of picking stations
μ_p	Picking efficiency of each picking station (i.e., the amount of picking per station per hour per unit time)
w_A	Width of single storage aisle
h_T	Height of single tier rack
l_s	Length of individual storage spaces
w_s	Width of single storage space
L_c	Total length of the conveyor line
$v_{s,A}$	Average speed of aisle shuttle(m/s)
$v_{s,C}$	Average speed of cross-aisle shuttle (m/s)
v_l	Average lift speed (m/s)
v_c	Average conveyor speed (m/s)
W_{shelf}	Width of storage shelf (m)
L_{shelf}	Length of storage shelf (m)
H_{shelf}	Height of storage rack (m)

C. OBJECTIVE FUNCTION

The total cost of the system includes three parts: the cost of aisle shuttle and cross-aisle shuttles, the cost of lifts, and the cost of shelves. Then the objective function 1 of the system cost is as follows:

$$C_{\min} = \left(C_{S,A} \cdot n_A + C_{S,C}\right) \cdot n_T + C_L \cdot n_P + C_s \cdot (2 \cdot n_T \cdot n_C \cdot n_A) \tag{1}$$

In this expression, $C_{S,A}$ is the unit price of the aisle shuttle, $C_{S,C}$ is the unit price for the cross-aisle shuttle, C_L is the unit price of a group of lifts, C_s is the shelf price for a single storage location.

The first part in (1) shows that is the total cost of the shuttle, the second part is the total cost of the lift, and the third part is the total cost of the three-dimensional rack. The unit price of shuttle trucks and lift is much higher than the shelf price of storage space. The number of all three is equal to the number of system aisles n_A, number of storage positions equals n_T, number of lifts n_P is related, then the variables of these three parameters will lead to changes in system costs.

Considering costs, we also have to achieve a maximum throughput of the system so that the target function of the maximum throughput of system 2 is:

$$\text{TPS}_{\max} = \min\left(\text{TPS}_A, \text{TPS}_C, \text{TPS}_L, \text{TPS}_P\right) \tag{2}$$

where:

$\text{TPS}_L, \text{TPS}_S, \text{TPS}_r$ represents the throughput capacity required by the lift, shuttle, and enterprise in the system.

The decision variable to be optimized is:

$$x = (n_T\, n_A\ , n_C,\ n_P) \tag{3}$$

Assume TPS_r is the maximum efficiency of the system that the customer needs at least. N_r is the storage capacity of the system required by the customer. T_r Picking cycle for an order completed by the system required by the customer.

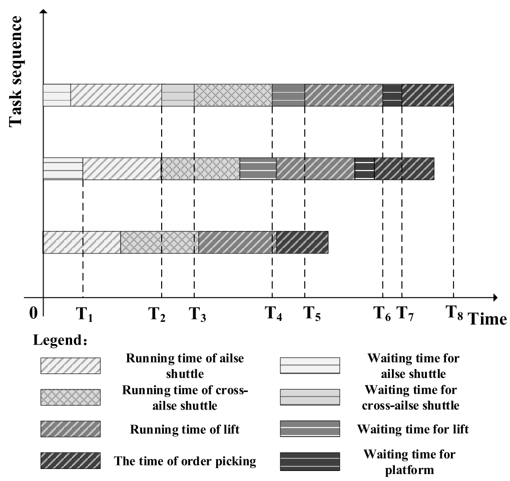


FIGURE 3. The operating time of shuttle and lift in CASBS/RS system.

Then make sure that

$$\text{TPS}_{\max} \geqslant \text{TPS}_r \tag{4}$$

$$2 \cdot n_A \cdot n_T \cdot n_C \geqslant N_r \tag{5}$$

$$T_0 \leqslant T_r \tag{6}$$

where:

T_0 represents the cycle time of picking an order.

In order to solve this problem easily, the multi-objective problem is transformed into a single-objective problem:

$$C_{\min} = \left(C_{S_A} \cdot n_A + C_{S_C}\right) \cdot n_T + C_L \cdot n_P + C_s \cdot (2 \cdot n_T \cdot n_C \cdot n_A) \tag{7}$$

$$S.T. \begin{cases} \text{TPS}_L \geqslant \text{TPS}_r \\ \text{TPS}_C \geqslant \text{TPS}_r \\ \text{TPS}_A \geqslant \text{TPS}_r \\ \text{TPS}_P \geqslant \text{TPS}_r \\ 2 \cdot n_A \cdot n_T \cdot n_C \geqslant N_r \\ T_0 \leqslant T_r \\ n_A, n_T, n_C, n_P \in (1, 2, 3, \ldots, n) \end{cases} \tag{8}$$

IV. ALGORITHMIC DESIGN

A. ANALYSIS OF SYSTE PERFORMANCE

The system's performance is mainly reflected in the cycle time of completing an order in the system. As shown in Fig.3, the order picking cycle of the system is equal to the total time of aisle shuttle, cross-aisle shuttle, lift, and waiting for aisle shuttle, cross-aisle shuttle, and lift. Then this chapter considers only the task of selecting the warehouse, and the calculation of the order picking cycle T_0 can be as follows:

$$T_0 = \sum_{i=1}^{8} T_i, \quad i = 1, 2, \ldots, 8 \tag{9}$$

T_1, T_3, T_5, T_7 in the model are respectively the time for picking orders waiting for aisle shuttle, the time for turnaround boxes waiting for the cross-aisle shuttle, the time

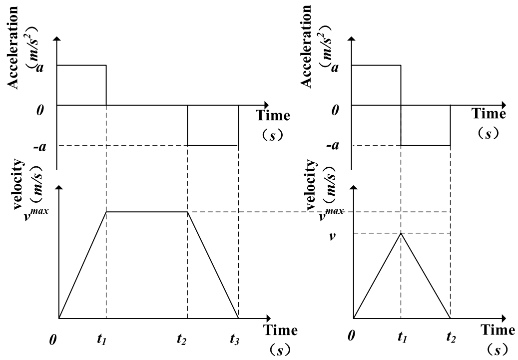


FIGURE 4. The operating time of shuttle and lift in CASBS/RS system.

for turnaround boxes waiting for lift service, and the time waiting for workers to pick in the buffer area, which is related to the arrival rate of the picking task, the sorting efficiency of the shuttle, lift and picking workstation and the capacity of the buffer area. Assuming that the waiting time for response is t_w and the current service equipment requests the next service is the n task, then the waiting time can be expressed as:

$$t_w = \begin{cases} T(n-1) - T'(n), & T'(n) < T(n-1) \\ 0, & T'(n) \geqslant T(n-1) \end{cases} \tag{10}$$

T_2 is the running time of the aisle shuttle, which includes the time from the outlet buffer zone to the target picking position (t_1), the time for the aisle shuttle to pick up the tote (t_2), the time for the aisle shuttle to transport the tote to the outlet buffer zone (t_3) and the time for the aisle shuttle to unload the tote (t_4). Where t_2 and t_4 are the same, both equal to t_p, referring to the time taken by the equipment (aisle shuttle, cross-aisle shuttle, and lift) to pick up or unload the turnaround box. Assume that the running distance of the aisle shuttle is $l(x)$ from the warehouse buffer to the target picking location:

$$l(x) = n_C(x) \cdot w_s \tag{11}$$

According to the motion characteristics of shuttle and lift are shown in Fig.4, the running time of aisle shuttle is:

$$t_1 = t_3 = t(x) = \begin{cases} 2 \cdot \dfrac{v_{s,A}}{a_{s_A}} + \dfrac{l(x) - \frac{v_{s,A}{}^2}{a_{s,A}}}{v_{s,A}}, & l(x) > \dfrac{v_{s,A}{}^2}{a_{s,A}} \\ 2\sqrt{\dfrac{l(x)}{a_{s,A}}}, & l(x) \leq \dfrac{v_{s,A}{}^2}{a_{s,A}} \end{cases} \tag{12}$$

Since the time for an aisle shuttle to complete a picking task is T_2, the maximum picking quantity TPS_A for aisle shuttle per unit time is:

$$\mathrm{TPS}_A = \frac{3600}{t_1 + t_2 + t_3 + t_4} \cdot n_A \cdot n_T \tag{13}$$

T_4 is the running time of the cross-aisle shuttle, which includes the travel time (t_5) of the cross-aisle shuttle from the current parking position to the target aisle, the time (t_6) it takes for the cross-aisle shuttle to retrieve the turnaround box from the outlet buffer, the time (t_7) it takes for the cross-aisle shuttle to transport the turnaround box to the corresponding lift and the time (t_8) it takes for the cross-aisle shuttle to unload the turnaround box. Similarly, $t_6 = t_8 = t_p$; and assume that the repository shuttle runs at a distance of $l(y)$:

$$l(y) = n_A(y) \cdot (w_A + 2l_s) \tag{14}$$

Then the running time of the cross-aisle shuttle is:

$$t_5 = t_7 = t(y) = \begin{cases} 2 \cdot \dfrac{v_{s,C}}{a_{s,C}} + \dfrac{l(y) - \frac{v_{s,C}{}^2}{a_{s,C}}}{v_{s,C}}, & l(y) > \dfrac{v_{s,C}{}^2}{a_{s,C}} \\ 2\sqrt{\dfrac{l(y)}{a_{s,C}}}, & l(y) \leq \dfrac{v_{s,C}{}^2}{a_{s,C}} \end{cases} \tag{15}$$

Since the cross-aisle shuttle takes T_4 to complete a picking task, the maximum reloads TPS_C per unit time of the cross-aisle shuttle is:

$$\mathrm{TPS}_C = \frac{3600}{t_5 + t_6 + t_7 + t_8} \cdot n_T \tag{16}$$

T_6 is the operating time of the lift. This time includes the time (t_9) taken by the lift from the first tier to the target tier, the time (t_{10}) taken by the lift to retrieve the tote from the output buffer, the time (t_{11}) taken by the lift to transport the tote to the first tier and the time (t_{12}) taken by the lift to unload the tote. Where $t_{10} = t_{12} = t_p$; and assuming the lift runs at a distance of $l(z)$: then,

$$l(z) = n_T(z) \cdot h_T \tag{17}$$

Then the lift runs for:

$$t_9 = t_{11} = t(z) = \begin{cases} 2 \cdot \dfrac{v_l}{a_l} + \dfrac{l(z) - \frac{v_l^2}{a_l}}{v_l}, & l(z) > \dfrac{v_l^2}{a_l} \\ 2\sqrt{\dfrac{l(z)}{a_l}}, & l(z) \leq \dfrac{v_l^2}{a_l} \end{cases} \tag{18}$$

In this expression: t_l refers to the time delay of lift due to acceleration and deceleration during operation (s).

Since the lift takes T_6 to complete a picking task, the maximum lift volume TPS_L per unit time is:

$$\mathrm{TPS}_L = \frac{3600}{t_9 + t_{10} + t_{11} + t_{12}} \cdot n_p \tag{19}$$

T_8 is the time for the picking station to carry out the picking operation, including the running time (t_{13}) of the turnaround box on the conveyor line and the time (t_{14}) required for the workers to carry out the picking operation, and the turnaround box is moving uniformly on the conveyor line. Then the maximum picking quantity of the picking platform is:

$$\mathrm{TPS}_P = \mu_p \cdot n_p \tag{20}$$

The sorting efficiency of the system refers to the sorting quantity of the system in a unit of time. Because each service organization (aisle shuttle, cross-aisle shuttle, and lift) operates relatively independently in the system and the processing time is different, there will be waiting time, which will interact. The equipment with the lowest efficiency will limit the maximum sorting capacity of the system. Then according to (13), (16), (19), (20), the maximum throughput of the system is:

$$TPS_{\max} = \min\left(TPS_A, TPS_C, TPS_L, TPS_P\right) \tag{21}$$

B. IMPROVED PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a biomimetic algorithm that simulates the foraging behavior of birds. It updates the speed and position of particles by sharing information between individual particles and groups. PSO algorithm belongs to the evolutionary algorithm. It searches for the best solution by iteration from random solution and evaluates the quality of solution by fitness.

Compared with other algorithms, the PSO algorithm has no crossover and mutation operations, relies on the particle speed to complete the search, and only the best particles in the iterative evolution transmit information to other particles, so the search speed is faster. PSO algorithm has memory. The best position in the history of particle swarm can be memorized and passed to other particles. The PSO algorithm needs to adjust fewer parameters, has a simple structure, and is easy to implement in engineering. PSO algorithm adopts real number coding, which is directly determined by the solution of the problem. The number of variables of the problem's solution is directly taken as the dimension of the particle.

Its algorithm rules are simpler. By following the best solution currently searched, this algorithm is easy to realize and converges quickly with high accuracy.

PSO is initialized as a group of random particles and the optimal solution is found by iteration. In each iteration, the particle updates itself by tracking two "extreme" ($p_{\text{best}}, g_{\text{best}}$). After finding two extremes, the particle updates its speed and position by using the following formula:

$$v_i = v_i + c_1 r_1 \left(p_{\text{best}} - x_i\right) + c_2 r_2 \left(g_{\text{best}} - x_i\right) \tag{22}$$

$$x_i = x_i + v_i \tag{23}$$

where v_i is the velocity of the particle, x_i is the current position of the particle, r_1 and r_2 are random numbers between (0,1), c_1 and c_2 are learning factors, and $c_1 = c_2 = 2$ is usually used. The first part of (22) represents the influence of the velocity and direction of the last particle; the second part indicates that the action of the particle originates from its own experience; and the third part is a vector pointing from the current point to the best of the population, reflecting the collaboration and knowledge sharing among the particles. Particles are the ones who determine their next movement through their own experience and the best of their peers.

The objective function in this section is to minimize the total cost of the system while meeting the required throughput and storage capacity. In the continuous iteration of the particle swarm algorithm, the extremum of each particle and the extremum of the particle swarm need to be replaced and retained. Usually, we take the inverse of the objective function as the fitness function, while the value of our objective function is relatively large. Therefore, to facilitate subsequent observation and comparison, the inverse of the objective function can be amplified 1000 times. The expression for calculating the fitness function of the n-th particle in the m-generation population is:

$$f_{m,n} = \frac{1000}{C_{m,n}} \tag{24}$$

In (24), $n \in \{1, 2, 3, \ldots, N\}$, N is the number of individuals per generation, $C_{m,n}$ is the minimum cost of the n-th particle of the m-th population.

C. OPTIMIZE INITIAL PARTICLE SWARM

Particle initialization parameters have a certain impact on the algorithm's performance in terms of detection capability, tracking accuracy and time complexity. We propose a heuristic algorithm to make the algorithm model perform more quickly and effectively for the problems raised in this chapter. We propose a heuristic algorithm to determine the initial particles based on the bottleneck of shuttle and lift in CASBS/RS. The initial particle $X_0(n_{T,0}, n_{A,0}, n_{C,0}, n_{P,0})$ is optimized below.

Step 1, one of the parameters n_T is determined. According to (1), it can be seen that in the system, aisle shuttle, cross-aisle shuttle, and high-speed lift account for a large proportion of costs, while aisle shuttle and cross-aisle shuttle are both n_T-related and proportional, so that n_T is minimized on the premise of satisfying the storage quantity N_r required by customers:

$$n_{T,\min} = \left\lceil \frac{N_r}{2 \cdot n_{A,\max} \cdot n_{C,\max}} \right\rceil \tag{25}$$

$$n_{A,\max} = \left\lfloor \frac{W_{\text{shelf},\max}}{w_A + 2\, l_s} \right\rfloor \tag{26}$$

$$n_{C,\max} = \left\lfloor \frac{L_{\text{shelf},\max}}{w_s} \right\rfloor \tag{27}$$

According to the throughput capacity required by the customer, the number of selector stations can be obtained:

$$n_P = \left\lceil \frac{TPS_r}{\mu_p} \right\rceil \tag{28}$$

Let $n_{T,0} = n_{T,\min}$ at this time, so:

$$n_{A,0} = \left\lceil \frac{N_r}{2 \cdot n_{T,0} \cdot n_{C,\max}} \right\rceil \tag{29}$$

$$n_{C,0} = \left\lceil \frac{N_r}{2 \cdot n_{T,0} \cdot n_{A,0}} \right\rceil \tag{30}$$

Obtain $X_0 = \left(n_{T,0}, n_{A,0}, n_{C,0}, n_{P,0}\right)$ as the decision variable.

Step 2, Evaluate this decision variable. The maximum picking quantity TPS_0 in unit time of the system can be obtained by (1). By comparing with the maximum picking quantity TPS_r in unit time of customer's demand, if $TPS_0 \geqslant TPS_r$ at this time, it proves that the system configuration can meet customer's demand this time, then this X_0 can be used as the initial particle. If $TPS_0 < TPS_r$ at this time, there is a bottleneck of low sorting efficiency in some parts of the system. Further analysis should be carried out in the third step to improve the sorting efficiency of the system and obtain better initial particles.

Step 3, equation (28) shows that the efficiency of the sorting table has met the efficiency required by customers, so only the throughput capacity of aisle shuttle, cross-aisle shuttle, and lift needs to be analyzed here. Through (13), (16), and (19), the throughput capacity of aisle shuttle, cross-aisle shuttle, and lift can be calculated as $TPS_{A,0}$, $TPS_{C,0}$, $TPS_{L,0}$, respectively. If $TPS_{\max,0} = \min(TPS_{A,0}, TPS_{C,0}, TPS_{L,0}, TPS_P0) = TPS_{A,0}$, Then the aisle shuttle is the bottleneck at this time, so we can consider increasing the number of tiers or increasing the number of aisles to improve the service efficiency of the aisle shuttle. First consider increasing the number of levels so that $n_{T,0} = n_{T,0} + 1$ is taken as the new $n_{T,0}$, then the corresponding number of aisles and bays can be obtained by (29), (30) as the new $n_{A,0}$, $n_{C,0}$.

If the number of tiers reaches the maximum limit, only the selected quantity of aisle shuttle can be increased by increasing the number of aisles without exceeding the limit of warehouse size. i.e., $n_{A,0} = n_{A,0} + 1$ and the number of shelves remains the same, then the latest number of bays $n_{C,0}$ can be found by (30).

If the aisle shuttle is not a bottleneck limiting the maximum throughput of the system, then consider whether the cross-aisle shuttle is a bottleneck at this time. If the cross-aisle shuttle is a bottleneck, i.e., $TPS_{\max,0} = TPS_{C,0}$, the number of tiers can be increased and the initial particles can be obtained according to the (29) and (30).

This section optimizes the initial particle swarm by introducing some heuristic rules. As shown in Fig.5, the basic steps of the improved algorithm are as follows:

Step 1: set the initialization parameters, particle swarm size, initialization speed, and the maximum number of iterations of the algorithm;

Step 2: optimizes the initialization particles to generate a specified number of initialization particle swarms;

Step 4: which replaces the individual extremes of the particles and updates the global optimum according to the fitness values of the particles;

Step 5: replacing the speed position of particles with adaptive weight coefficient and learning factor;

Step 6: if the maximum number of iterations is satisfied, then the optimal result is output. otherwise, go to step 3.

V. SIMULATION AND EXAMPLE

A. SIMULATION ANALYSIS

In order to verify the validity of the model and algorithm proposed in this section, simulation tests are carried out according to the characteristics and parameters of the mechanical structure of the system in actual projects. All the experiments were performed on the computer with 8.00G memory of

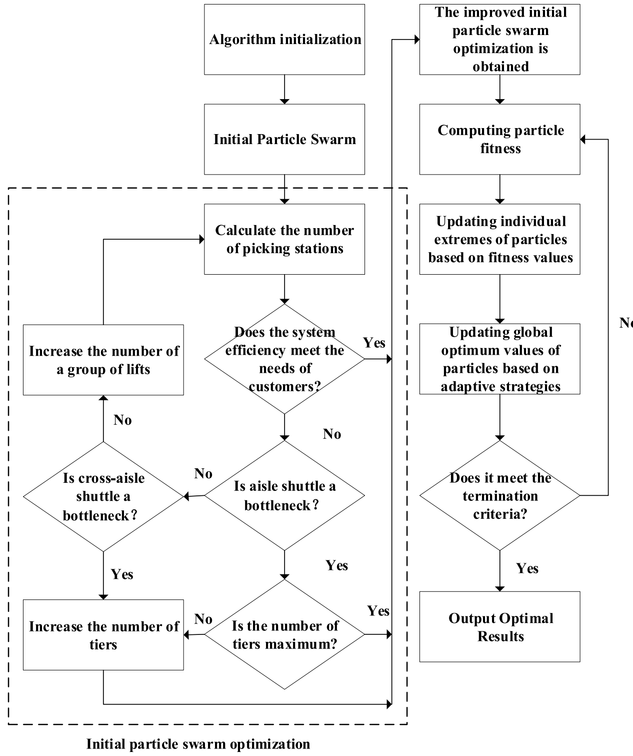


FIGURE 5. The solving process of Improved Particle Swarm Optimization.

Inter (R) Core (TM) i5-3210M CPU @2.50GHz dual-core processor, and the algorithm was completed on MATLAB 2019b.

In this paper, CASBS/RS is taken as the research object, and three simulation experiments are carried out. The first experiment is the comparison before and after the improvement of the particle swarm optimization algorithm. The second experiment uses the improved particle swarm optimization algorithm to solve different objective functions to get feasible solutions. The third test is the optimal configuration of the system in 70 different situations.

1) THE FIRST EXPERIMENT

The CASBS/RS system is selected as the test object. The maximum number of iterations that the improved particle swarm algorithm and the standard particle swarm algorithm satisfy the termination conditions is 200 times. The particle number N of each generation is 30. The maximum speed of the particles is 0.01 times the product of tiers n_T, aisles n_A and bays n_C in the system. The mean values of learning factors c_1 and c_2 equal 1. Assuming $N_r = 10000$, $TPS_r = 1500$, the values of other parameters are shown in Table 1 and Table 2.

The particle swarm optimization algorithm before and after the improvement is run 50 times. The results of searching for the best solution by the two algorithms are counted in Table 3. And, the iterative process of the two algorithms is shown in Figure 6.

TABLE 1. **The value of system parameters.**

System parameters	value
Length of a single storage location (m)	0.8
Width of a single storage location (m)	0.8
Width of a single aisle (m)	1.4
Height of single shelf (m)	0.8
Maximum speed of aisle shuttle (m/s)	2
Maximum speed of crosee-aisle shuttle (m/s)	3
Maximum speed of lift (m/s)	6
Acceleration of aisle shuttle (m/s^2)	2
Acceleration of crosee-aisle shuttle (m/s^2)	2
Acceleration of lift (m/s^2)	3
Length of conveyor line (m)	4
Throughput of single picking platform (/h)	360
Average conveying speed of conveyor line (m/s)	0.7
Time to pick up or unload the tote (s)	2

TABLE 2. **Price of equipment.**

Equipment	price (million)
Unit price of aisle shuttle	15
Unit price of cross-aisle shuttle	15
Unit price of a group of lift	30
Unit price of storage location	0.04

TABLE 3. **Comparison of optimization results.**

Algorithm	Number of tests				
	1	2	3	4	5
PSO	731.04	730.32	685.48	731.04	730.32
IPSO	685.48	685.48	685.48	685.48	685.48
	6	7	8	9	10
PSO	730.32	685.48	731.04	730.32	685.48
IPSO	730.32	685.48	685.48	685.48	685.48
	11	12	13	14	15
PSO	731.04	730.32	685.48	776.6	790.96
IPSO	685.48	685.48	685.48	685.48	730.32
	16	17	18	19	20
PSO	730.32	685.48	731.04	730.32	685.48
IPSO	685.48	685.48	685.48	685.48	685.48
	21	22	23	24	25
PSO	731.04	730.32	685.48	776.6	790.96
IPSO	685.48	685.48	730.32	685.48	685.48
	26	27	28	29	30
PSO	731.04	730.32	685.48	731.04	730.32
IPSO	685.48	685.48	685.48	685.48	685.48
	31	32	33	34	35
PSO	730.32	685.48	731.04	730.32	685.48
IPSO	685.48	730.32	685.48	685.48	685.48
	36	37	38	39	40
PSO	730.32	685.48	776.6	790.96	730.32
IPSO	685.48	685.48	685.48	685.48	685.48
	41	42	43	44	45
PSO	790.96	730.32	731.04	730.32	685.48
IPSO	730.32	685.48	685.48	685.48	685.48
	46	47	48	49	50
PSO	730.32	731.04	730.32	685.48	776.6
IPSO	685.48	685.48	685.48	685.48	730.32

To make a more comprehensive comparison between the two improved algorithms. Run 50 times in 10 different situations without restricting the number of iterations, and the termination condition is the convergence of the result. The purpose of running 50 times in each case is to ensure the accuracy of the results. We then averaged the number of iterations over the 50 runs. By counting the results of 1000 times experiments, we compare iteration times in 10 different cases, as shown in Table 4.

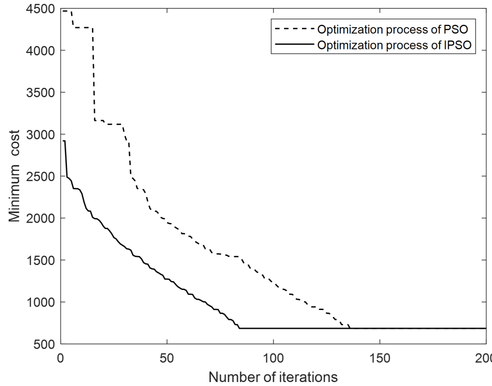


FIGURE 6. **The Comparison of PSO and IPSO in optimization process.**

TABLE 4. **Comparison of algorithm iterations in different cases.**

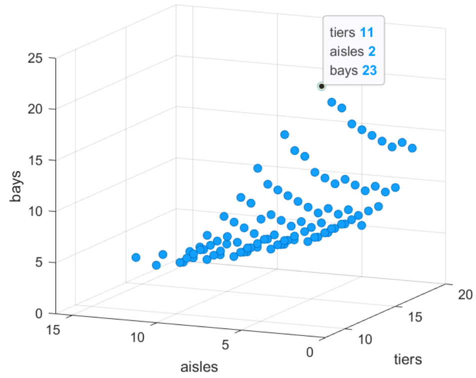
Throughput	Algorithm	Quantity of storage locations				
		1000	2000	3000	4000	5000
500	PSO	35	89	135	187	223
	IPSO	11	23	37	53	81
1000	PSO	57	129	194	234	267
	IPSO	24	33	53	77	93

2) THE SECOND EXPERIMENT

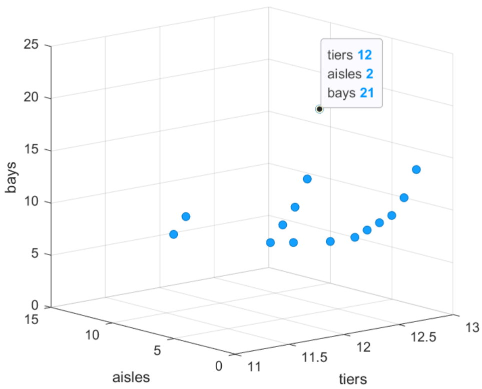
The setting of the main parameters of the system is shown in Table 1. Other assumptions of the system are consistent with the model; that is, the random storage strategy follows POSC and FCFS. To study the optimal configuration of the system and further verify the accuracy of the theoretical model, we set up the second experiment from the following three cases. They are ($N_r = 1000, \mathrm{TPS}_r = 1500$), ($N_r = 1000, \mathrm{TPS}_r = 2500$), and ($N_r = 3000, \mathrm{TPS}_r = 2500$).

The throughput of the system considered in this test, i.e. ($1500h^{-1}, 2500h^{-1}, 2500h^{-1}$), then the output of the corresponding picking station is 1500, 2500 and 2500, Then according to $n_p = \left\lceil \frac{\mathrm{TPS}_r}{\mu_p} \right\rceil$ i.e., the number of picking stations corresponds to 5, 7, and 7 respectively, the decision variable is transformed into $X\ (n_T, n_A, n_C)$.

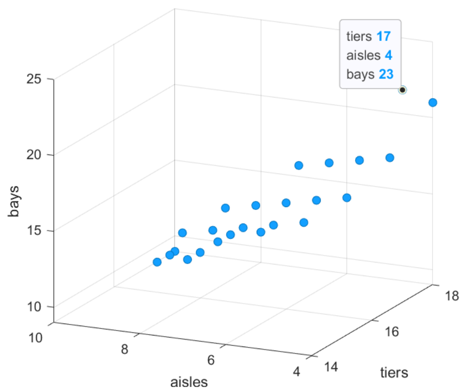
The feasible solution set of the current function under different conditions as shown in Fig.7 is obtained by simulation for three cases. Since in the case of $N_r = 3000$ and $\mathrm{TPS}_r = 2500$, when the number of lifts equals to the number of picking tables equals 7, there is no feasible solution for the objective function, Then the number of sorting tables is optimized to 8 through the optimization steps for initial particles, so the optimal solutions for the system in these three



(a) Storage Quantity:1000, throughput:1500



(b) Storage Quantity:1000, throughput:2500



(c) Storage Quantity:3000, throughput:2500

FIGURE 7. **Set of feasible solutions for objective function under different conditions.**

cases are $x = (11\,2\,23, 5)$, $x = (12\,2\,21, 7)$, $x = (17\,4\,23, 8)$ by the final solution.

3) THE THIRD EXPERIMENT

To further explore the relationship between system throughput capacity, storage capacity, and cost in CASBS/RS system. Set the system capacity required by the customer to $N_r \in (1000, 2000, 3000, \ldots, 10\,000)$ below, The throughput per unit time of the system needed by the customer is $\mathrm{TPS}_r \in (500, 1000, 1500, \ldots, 3500)$.

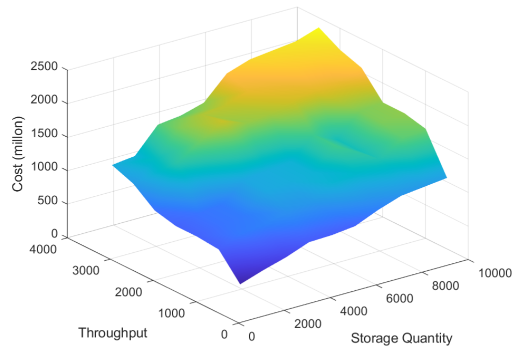


FIGURE 8. **The trend in total cost of the system.**

Through 50 tests and averaging each of the above 70 cases in the model, the optimal solution is shown in Table 5 and Fig. 8.

B. DISCUSSION ON SIMULATION RESULTS

As shown in Table 3, it can be seen that the standard particle swarm algorithm only finds global optimum solutions 685.48 13 times in the process of searching for the best solution in 200 iterations. In comparison, the improved particle swarm algorithm finds global solutions 685.48 44 times to search for the best solution in 200 iterations. There is no doubt that the improved particle swarm algorithm can search for the optimal solution globally and better stability than the standard particle swarm algorithm.

By comparing the process of searching the optimal solution between the PSO algorithm and IPSO algorithm in Fig. 6, it can be seen that compared with the PSO algorithm, the IPSO algorithm improves the quality of the initial particle swarm and approaches the optimal global solution more quickly in the process of iteration, and converges to the minimum value when the number of iterations reaches the 84th generation. In contrast, the PSO algorithm converges to the minimum value only in the 136th generation.

And Table 4 also shows that under ten different customer demand conditions, the number of iterations of the IPSO algorithm is less than that of the PSO algorithm. So, through the first experiment, it can be concluded that the initial particle swarm optimization method can make the algorithm converge faster and has higher stability than the traditional particle swarm optimization method, which makes the results of the algorithm more accurate.

The results of Experiment 2 are shown in Fig. 7. From the position of the optimal solution in the feasible solution, it can be seen that the situation of small system cost needs to satisfy two conditions: a large number of bays and the small number of aisles at the same time. In designing the system, bay and aisle layouts can be considered preferentially without exceeding the limits of warehouse size and with maximum throughput capacity to meet customer requirements.

In the last experiment, it can be seen from Table 5 and Fig. 8 that the construction cost of the system will increase

TABLE 5. Optimal allocation of system.

Throughput	Parameter	Quantity of storage locations									
		1000	2000	3000	4000	5000	6000	7000	8000	9000	10 000
500	tiers	5	5	4	5	4	4	5	5	5	5
	aisles	2	3	5	5	6	6	6	7	7	7
	bays	50	67	75	80	105	125	117	115	129	143
	lifst	2	2	2	2	2	2	2	2	2	2
	cost	325	440	540	670	682	720	866	982	1021	1060
1000	tiers	6	7	7	7	8	8	8	8	9	9
	aisles	3	3	3	4	4	4	5	5	5	5
	bays	28	48	72	72	79	94	88	100	100	112
	lift	3	3	3	3	3	3	3	3	3	3
	cost	685	832	870	971	1011	1218	1257	1373	1590	1633
1500	tiers	11	10	10	11	11	11	11	12	12	12
	aisles	2	3	3	3	3	4	4	4	5	5
	bays	23	34	50	61	76	69	80	84	75	84
	lift	5	5	5	5	5	5	5	5	5	5
	cost	715	800	841	1122	1163	1200	1512	1343	1665	1708
2000	tiers	11	12	12	13	13	13	14	14	15	15
	aisles	2	2	2	3	3	3	4	3	4	4
	bays	23	42	63	52	65	77	63	96	75	84
	lift	6	6	6	6	6	6	6	6	6	6
	cost	716	801	841	1122	1163	1200	1512	1342	1665	1708
2500	tiers	12	15	17	16	17	17	18	18	18	19
	aisles	2	4	4	5	4	4	4	4	4	4
	bays	21	17	23	25	37	45	49	56	63	66
	lift	7	7	8	8	8	8	8	8	8	8
	cost	790	1417	1640	1840	1716	1760	1872	1913	1953	2066
3000	tiers	16	16	17	18	18	19	19	20	20	20
	aisles	2	3	4	4	4	4	4	4	4	4
	bays	16	21	23	28	35	40	47	50	57	63
	lift	9	9	9	9	9	9	9	9	9	9
	cost	1031	1311	1670	1781	1822	1938	1981	2090	2135	2173
3500	tiers	18	18	19	19	20	20	21	21	21	22
	aisles	2	2	3	3	3	4	4	4	4	4
	bays	14	28	27	36	42	38	42	48	54	57
	lifts	10	10	10	10	10	10	10	10	10	10
	costs	1150	1190	1563	1604	1702	2043	2157	2198	2238	2351

with the continuous improvement of the number of cargos and the requirement of the system's picking ability per unit time. When designing a system, it is necessary to thoroughly study the throughput capacity required by the customer and properly configure the system's structure and shuttle and lift, thus never reducing the input cost.

C. EXAMPLE

This part of the data is from the actual situation, mainly from a well-known B2C e-commerce company in China. Its regional distribution center adopts CASBS/RS that shuttles can cross aisles. It is designed by a renowned domestic listed company focusing on the development of logistics automation facilities.

By analyzing one year's actual orders of e-commerce companies, we find that the customer orders of e-commerce companies are characterized by many varieties, small batches, and many frequencies. And the daily average picking volume is more significant than other companies. The analysis shows that the E-commerce company requires the sorting capacity of the system in unit time of 2000/h, and the size of the warehouse limits the length, width, and height of the storage shelf to 100m, 30m, and 10m. Based on the size of the turnaround box, the sizes of the designed shelf are $h_T = 0.8$m, $l_s = 0.8$m, $w_s = 0.8$m, Depending on the warehouse constraints, the parameters of the system can be configured in accordance with the following conditions: $n_T \leqslant 12, n_A \leqslant 10, n_C \leqslant 125$.

Due to the limitation of warehouse size, the level height can't exceed 12 tiers. only the number of aisles and the number of lifts can be increased to ensure the maximum throughput capacity of the system. Through the feasible solution obtained in Table 5, it can be concluded that the best configuration scheme of the E-Commerce company's system is 8 tiers, 7 aisles, 90 bays, 7 selection platforms, and 7 lifts. The actual operation shows that the results are in accordance with the actual design.

VI. CONCLUSION

This paper introduces the composition and layout of the system. Combined with the single instruction operation process, we analyze the operation time of the leading equipment in the system. And an improved particle swarm optimization algorithm is proposed to minimize the construction cost of the system under specific sorting and storage capacity conditions. In solving, the initial particles are optimized. The relationship between the system cost and the system configuration and the relationship between the system cost and the system storage capacity, and the system throughput capacity is obtained by simulation. However, this paper does not study other aspects of the algorithm, such as improving fitness function. It is worth further research to solve the system design problems of different algorithms.

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