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Path Planning of Multi-AGVs for Auto-Sorting Using Time Window Searching

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Abstract With the booming development of online shopping, a massive number of commodities have to be delivered to customers in different regions through express mail. It brings a new challenge that modern logistics center must promote its sorting ability in a more automated way rather than artificially. In this paper, we study the problem of path planning of multi-AGVs (automated guided vehicles) for automatic sorting in logistics center. Given the warehouse map of logistics center, our goal is to transport as many cargoes as possible from different imports to the designated exports using the smallest possible number of AGVs within given period. To solve the problem, we abstract the actual warehouse map into a directed graph, based on which we give the description of our problem. We propose two heuristic algorithms to search for available free time windows of the blocks that each AGV can pass through along its selected path without collision. Experiments show that our methods are more efficient than existing work with higher sorting throughput within given time while using less vehicles.

Keywords Multi-AGVs · Automatic Sorting · Path Planning

1 Introduction

The vigorous development of e-commerce has already changed people's shopping habits, and there can be hundreds of thousands of commodities delivered by express mail every day. As a result, the logistic centers of those express companies have to face the challenge of packages sorting with so large number

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that is almost impossible to be completed by traditional human labor. Therefore, AGVs (automated guided vehicles) are gaining increasing attentions in modern logistics centers, since they can automatically and efficiently transport cargoes from different imports to the corresponding sorting destinations in a collaborative way without collision. However, exploring feasible paths for multiple AGVs is not so easy, because the search space grows exponentially with the increase of the number of vehicles and the complex influence of the path choices of previous vehicles on the motions of the following ones [26,32].

In this paper, we aim at finding effective paths of AGVs, so that the sorting throughput can be maximized while using as few vehicles as possible within given time. For ease of modeling, the warehouse map is divided into square blocks, some of which are used as passable road for vehicles, while others represent imports, exports, or temporary buffers that are used to avoid traffic congestion. Thus, the actual warehouse map can be abstracted into a directed graph with vertexes representing the passable blocks. For each block, it can accommodate only one AGV in a time window. Note that, there may exist collisions when two or more vehicles have the same blocks to pass through in the same time window, which can be avoided using wait-and-go policy. Our problem is NP hard with large-scale search space that can not be solved using existing optimization tools [9]. To solve this problem, we first generate a set of potential candidate paths for each AGV using improved penalized A* algorithm, and then select the one with earliest arrival time window and make reservation for this path. Once reserved, the time windows of the blocks along this path can not be used by the any other AGVs at the same time. We propose two different heuristic algorithms F-TWS and RS-TWS to search for available free time windows of the blocks that each AGV can pass through along its selected path. Experiments show that our methods are more efficient than existing work with higher sorting throughput within given time while using less vehicles under different layouts of warehouse.

The rest of this paper is organized as follows. In Section 2, state-of-the-art works in literature are reviewed. We describe our problem based on the abstracted directed graph in Section 3. After that, our approaches are presented in Section 4. In Section 5, we setup experiments and make analysis of the results. Finally, we conclude the whole paper in Section 6.

2 Related Work

In general, existing work on path planning of multi-AGVs can be classified into two categories: centralized (or coupled) and decentralized approaches.

2.1 Centralized Approaches

For centralized approach, all AGVs are scheduled by a centralized controller that constantly gathers the environment information in real time and makes decisions on path planning with consideration of collision avoidance [21,31].

The advantage of the centralized methods is that the optimal schedule can be obtained when the problem scale is not so large, but their computational complexity will increase exponentially with scale, needing more calculating time for the controller. In general, there are three types of centralized approaches, including complete methods, layered methods, and intelligent methods.

A) Complete Methods

To get optimal path planning for AGVs, some complete algorithms based on linear programming model are studied in [15,10,5,30]. Yu et al. studied the optimal multi-robot path planning on graphs and formulated an ILP model [41]. They solved the problem using existing ILP solver and introduced a principled heuristics to improve the performance. In [11], MIP models are employed to encode the robot interactions. Nish et al. proposed a distributed path planning method for AGVs using the augmented Lagrangian decomposition and coordination technique [20]. The above methods can solve the problem in high quality, but cannot deal with large plant using many more AGVs.

B) Layered Methods

The searching space of multi-AGVs routing can be reduced using layered structure. As done in [23], they divided the global environment into sub-regions (cells) in the lower layer within which conflicts are solved, while constructing a virtual map consisting of region cells in the upper layer and path planning are made in it. Ryan et al. in [27] introduced the concept of sub-graph decomposition to cope with large searching space of multi-robot path planning. They decomposes the roadmap into sub-graphs of known structures like stacks or cliques and builds paths between connected sub-graphs, then plan paths inside each sub-graph. They also proposed a new sub-graph structure called hall to decompose global roadmap [28] to be more practical.

C) Intelligent Methods

Path planning based on computational intelligence has attracted more and more research interests to deal with unknown or dynamic environments [47, 19,24]. Wang et al. in [36] proposed a time window based A* algorithm using earliest arrival time as heuristic function rather than distance. This method can run quickly to find path but with too many failures. Zeng et al. gave a solution using HTN based planning [43]. The algorithm searches the surrounding passable area iteratively and returns infeasibility when meeting conflicts. Though this approach can manage the conflict situations and time constrains well, it performs poorly with the increase of AGV scale. In [45], a constrained multi-objective path planning algorithm based on particle swarm optimization is developed for robot navigation in uncertain environments. Konar et al. in [16] have applied Q-learning on robots to plan paths. Genetic algorithm (GA) is also adopted to plan conflict-free paths for AGVs [22,39,17]. An obstacle avoidance algorithm was proposed by Yun et al. to generate the initial population of GA [42]. To overcome the premature convergence in the traditional genetic algorithm, Hu et al. proposed a SAGA strategy to generate

the genetic operator which can get faster convergence than original GA [14]. However, with the number of AGV and plant scale grows, these algorithms will be computation expensive and impractical for applications.

2.2 Decentralized Approaches

Decentralized algorithms are proposed to speed up the AGV path planning in large-scale scenario, in which each AGV determines its own path and avoids conflicts through negotiating with nearby AGVs [12,46]. This strategy does not require complete system information so that it can be applied to the unknown environment exploration or partial observation losses [35]. The searching space of decentralized methods is always incomplete and there exists an obvious gap in system throughput compared with centralized approaches due to path finding failures caused by deadlocks. In spite of this, decentralized techniques are generally faster than centralized strategies [44].

Dewilde et al. in [8] proposed a rule based planning algorithm that defines a set of traffic rules to reduce computational complexity and guarantee the completeness at the cost of solution quality. Scerri et al. in [29] proposed a deconfliction strategy in which the AGVs are divided into many local teams, each team makes consensus on conflicts-free motion planning of its team member via token exchange. However this approach only suits for sparse environments. Purwin et al. in [25] proposed a local region reserve approach where AGV make reservations on regions of global map to move in, other vehicles which want to travel into these regions need to negotiate with that AGV. This strategy allows each AGV plans its path asynchronously but it's difficult to determine a proper local region size. Collisions along intersecting paths can be avoided by using reachability based planning approaches. In [13,7,1] the reachability based methods have been thoroughly studied. However, these methods are typically designed to coordinate non-cooperative vehicles, thus unsuitable for common scenarios. Li in [18] proposed a priority based method, in which the robots are prioritized and the planning problem is divided into a series of sub-steps for each robot. At each planning sub-step for one robot, other robots with higher priorities are considered as obstacles. The order of prioritizing of AGVs in priority based approaches is very important that can influence the planning results. The assignment of priorities to the robots is intensively studied in [34]. Wang et al. in [37] proposed an adaptive priority re-assignment idea in AGV routing, but the algorithm often fails to find valid routes and far from optimal. Therefore, they later improved their algorithm by proposing a Guided Iterative Prioritized Planning strategy, but at the expense of more computing time due to algorithm complexity [38].

2.3 Discussions

The above mentioned work concern only one loop of vehicles' planning. Once finished delivering the goods, the vehicles will be in idle position (or parking lot), which cannot be directly applied to the real logistic sorting scenario with

uninterrupted transportation. Moreover, most of the scheduling in literature are designed specifically for the predefined layout of the warehouses with no consideration of universality. In our work, we conquered the two drawbacks by proposing two strategies that can plan and coordinate a large number of AGVs back and forth for a long term, even under different warehouse layout scenarios. To optimize the path planning, we generate a set of potential candidate paths using penalizing like that in [3], which proved to be more efficient than k-shortest paths [40], k-disjoint path [33], Pareto [6], and Plateau [2].

3 Problem Description

3.1 Modeling of Layout into A Directed Graph

For a logistics sorting center, we first need to abstract its layout into a directed graph before path planning. For ease of modeling, the layout is divided into square blocks of the same size, which are abstracted as a point in the graph. There are directed arcs connecting the adjacent points with unit moving distance of an AGV. In each time slot, one block can be occupied by only one AGV. Fig. 1 is an example showing the modeling of directed graph.

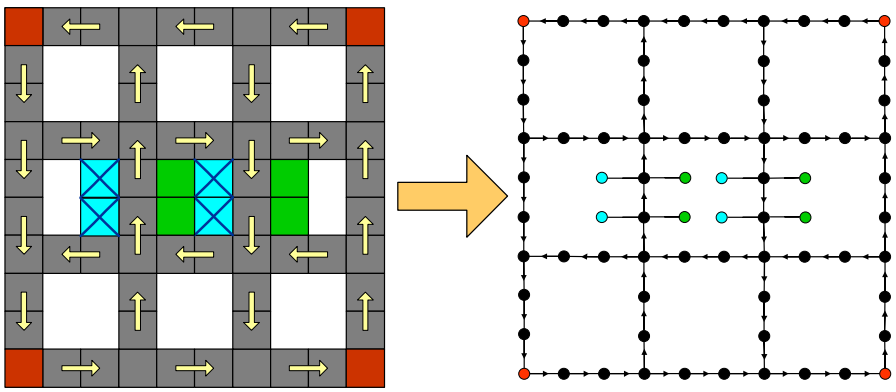

Fig. 1 The modeling of warehouse layout into a directed graph.

There are four types of blocks in the warehouse: Red blocks represent the imports (or called start blocks), where multiple AGVs are scheduled to load up express packages. Blue blocks represent sorting exports. In practice, the sorting block can be a hole with a collection bag, so that the AGVs will stop on the adjacent passable block to dump the carried package into its target hole. We use grey blocks to represent passable blocks for AGVs to pass through, which can accommodate only one AGV in each time slot. Green blocks represent buffer for AGVs to temporarily stop and avoid collisions. The traveling direction of each block is predefined for AGVs to go along. Note

that, the unused blocks with white color in the layout are reserved for future extension. Our scheduling focus only on the above four types of blocks.

3.2 Problem Description

Given the warehouse layout of logistics center, our goal is to transport as many cargoes as possible from different imports to the designated exports using the smallest possible number of AGVs within given period. We make the following assumptions for our problem of path planning of multi-AGVs:

1) All AGVs are homogeneous with constant velocity. We do not consider vehicle acceleration, deceleration or turning factor.
2) Each AGV can only carry one package in each delivery, and each passable block can be occupied by at most one AGV in a time slot.
3) It will take one time slot to dump (or offload) one package into export hole. After that, the AGV will return back for the next delivery.
4) If AGV fails to find a valid path in the loading point, it will wait until the path blocks are all available. A special case occurs when AGV have just finished package delivery and find no valid path, it shall go to buffer blocks to avoid congestion until there is valid path with all blocks available.

4 Algorithm Design

The notations to be used in this paper are listed in Table 1.

Table 1 Notations

Notation	Definition
T	The total running time slots, for each $t \in \{1, 2, ..., T\}$
K	Set of AGVs, for each $k \in K$
S_k	Starting block of AGV k in current scheduling
D_k	Destination block of AGV k in current scheduling
B_{pass}	Set of all passable blocks in the layout
$B_{succ}(i, p_k)$	Successor of block i on path p_k
$B_{pre}(i, p_k)$	Precursor of block i on path p_k
$w_{i,m}$	The $\boldsymbol{m}$th free time window for block i to pass through, $w_{i,m} = [t^s_{i,m}, t^e_{i,m}]$
$t^s_{i,m}, t^e_{i,m}$	The start and end time of the free time window $w_{i,m}$
$FTW_i(t)$	Set of free time windows of block i in t, $FTW_i(t) = \{w_{i,1}, w_{i,2}, ..., w_{i,m}\}$
$RFTW_{i,j}(t)$	Set of reachable free time windows from block i to block j in time slot t
$Sch(p_k)$	Schedule path of AGV k, $Sch(p_k) = ((S_k, t_{S_k}), ..., (i, t_i), (j, t_j), ..., (D_k, t_{D_k}))$
(i, t_i)	Tuple of block i and its corresponding entry time slot t_i

4.1 Overview of Our Algorithms

The objective of AGV path planning is to maximize the auto-sorting throughput, which is defined as the total number of successful deliveries of express packages into the export holes within given period. In real scheduling, there

may exist collisions when more than one AGVs wanting to pass through the same block at the same time. To avoid this, the path planned for each AGV involves not only the blocks to move along, but also the corresponding passable time slot of each block in the path, which is defined in the following:

Definition 1: Schedule-Path ($Sch(p_k)$) is the routing path of AGV k when its start block and destination block are given. It can be described by a sequence of passable block-time pairs $((S_k, t_{S_k}), ..., (i, t_i), (j, t_j), ..., (D_k, t_{D_k}))$. Note that, here the *destination block* refers to the nearest passable block that can dump packages into the export hole.

To enhance sorting throughput, the AGVs will constantly be scheduled back and forth to make deliveries between start blocks and destination blocks. To simplify this problem, we decompose one cycle of AGV delivery (from start block to destination and then return back) into two equivalent single-directed schedules, each having different start blocks and destination blocks, which can be planned separately. The start block and destination block will be updated after successfully delivering the package or returning back to the original start block. Thus, we only focus on the single-directed schedules of each AGV in our path planning, which can be solved in three steps as follows:

Step 1: Generating candidate paths before scheduling each AGV.

Step 2: Calculate the *schedule-path* for each candidate path by searching the passable time windows of the blocks in the path.

Step 3: Select the earliest arrival path and make reservation.

Algorithm 1: Path Planning for Single-directed Schedule of AGV

Input: The layout graph G, start time t of AGV k, its start block S_k and destination block D_k.
Output: Schedule-path for AGV k.

Initination: $failNum \leftarrow 0$; $failPaths \leftarrow \varnothing$; $SchPaths \leftarrow \varnothing$;
while $failNum < maxFails$ **do**
  $Paths \leftarrow$ generateCandidatePaths $(G, S_k, D_k, failPaths)$;
  foreach $p_k \in Paths$ **do**
    $twp_k \leftarrow$ timeWindowSearching (p_k, t);
    if $twp_k \neq infeasibility$ **then**
      $SchPaths \leftarrow SchPaths \cup twp_k$;
  if $SchPaths \neq \varnothing$ **then**
    $currentRoute \leftarrow$ selectEarliesArrival($SchPaths$);
    makeReservation($currentRoute$) ;
    return $currentRoute$;
  else
    $failNum \leftarrow failNum + 1$;
    $failPaths \leftarrow failPaths \cup Paths$;
return $\varnothing$;

Algorithm 1 shows the path planning of one AGV in a single-directed schedule. In fact, there may exist failure in time window searching for schedule-path from the generated candidate paths, so we set a maximum failure count $maxFails$ to repeat this process until finding feasible schedule-path(s) or all loops complete with no schedule-path found (Line2∼Line15). For each loop, we first generate a set of candidate paths (Line3). Then, calculate the schedule-path for each candidate path and add it to the schedule-path set (Line4∼Line7). If there are any schedule-path(s) found in this round of search, we select the one with earliest reaching time to the destination block, and then make reservation and output the best schedule-path (Line8∼Line11). Else, all candidate paths will be added to the set of failure path, so that the same path will not be used as candidate paths in the following loops of searching. If all loops of tryings fail, the output is empty (Line 15). In this condition, the AGV with no schedule-path will stop and wait in current block in time slot t. We will continue to search the schedule-path for this AGV with the same start and destination block in time slot $t + 1$.

4.2 Candidate Path Generation

To obtain the schedule-path for AGV, we first generate multiple candidate paths for AGV, based on which to make searching of the passable time windows. The main reason is that the shortest path may not always be the best one with earliest arrival time considering the time occupation of the blocks in the path by other AGVs through reservation in advance. Therefore, we propose a penalty based A* algorithm to generate candidate paths, as can be seen in Algorithm 2.

Algorithm 2: Generating Candidate Paths for AGV

Input: Layout Graph G, number of candidate paths N, start block S_k and destination block D_k of AGV k, and failed paths set $failPaths$.
Output: Set of candidate paths $Paths$.

```
1  Initination: Paths ← ∅; failCount ← 0;
2  foreach block i ∈ B_pass do
3      weight(i) ← 1;
4  while |Paths|<N  &&  failCount<maxFailCount do
5      p_k ← generatePath(G, S_k, D_k, weight); // Using A* Search
6      if p_k ∉ Paths ∪ failPaths then
7          Paths ← Paths ∪ p_k;
8          failCount ← 0;
9          foreach block i ∈ p_k do
10             α ← random(0,1);
11             if α < penaltyRatio then
12                 weight(i) ← weight(i) × penalty;
13     else
14         failCount ← failCount + 1;
15 return Paths;
```

In this algorithm, we try to generate N candidate paths (Line4∼Line14). Each passable block in the graph has a weight, as initialized to be 1 in (Line2∼Line3). We use penalty to change the weight of each block so as to affect the path searching in A*, which always selects the blocks with lower weight to avoid repeated selection of the same blocks among different candidate paths. In general, the weight of the blocks appearing in multiple paths will be more likely to have higher weight. For each generated candidate path, the weight of its blocks will be increased by multiplying a penalty value with probability of *penaltyRatio* between 0 and 1, as shown in (Line9∼Line12). It also means that the percentage of the number of the blocks to be updated in this path accounts for *penaltyRatio* roughly. Sometimes, A* algorithm cannot find any path not in existing path set, so our algorithm will be completed when there are $maxFailCount$ searching failures happening in a consecutive way (Line4, Line13∼Line14).

4.3 Time Window Searching: F-TWS and RS-TWS

In this section, we will give two algorithms of time window searching based on the generated candidate paths to build schedule-paths for AGV, including: forward time window searching and re-selection time window searching.

A) Preliminaries

Definition 2: Free Time Window. In each time slot t, the reservations (occupations) of block i during the whole period is discrete, leaving disjoint time intervals free. We call the set of such intervals as free time windows of block i, denoted as $FTW_i(t)$, for each time window $w_{i,m} \in FTW_i(t)$.

Definition 3: Reachable Free Time Window. For block i in time slot $t \in w_{i,m}$, the reachable free time windows of $w_{i,m}$ is the set of time windows belonging to $FTW_j(t)$ that should satisfy:
1) block j is the successor block of i on the path.
2) $\exists w_{j,n} \in FTW_j(t)$ such that $t+1 \in w_{j,n}$ or $t^e_{i,m}+1 \in w_{j,n}$, where $t^e_{i,m}$ is the last time slot of $w_{i,m}$.

Fig. 2(a) is an example to show the reachable free time windows for block i in time slot t. We suppose block j is the successor of time slot i. The corresponding free time window of time slot t is $w_{i,1}$. Based on the definition of RFTW, there are totally two reachable free time windows of block i in t:
1) Starting from $t \in w_{i,1}$, we can find a time window $w_{j,1}$, in which $t+1 \in w_{j,1}$.
2) Starting from $t+7 \in w_{i,1}$, we can find a time window $w_{j,2}$, in which $t+8 \in w_{j,2}$.
It's not difficult to find that the $RFTW_i(t)$ has the property of time continuity with the time window that contains t.

Fig. 2(b) is an example to show time window search process. Given the candidate path from block 0 to block 2, denoted as $p_k = (0, 1, 2)$, with start time $t = 1$. Our goal is to find a schedule-path with earliest arrival time.

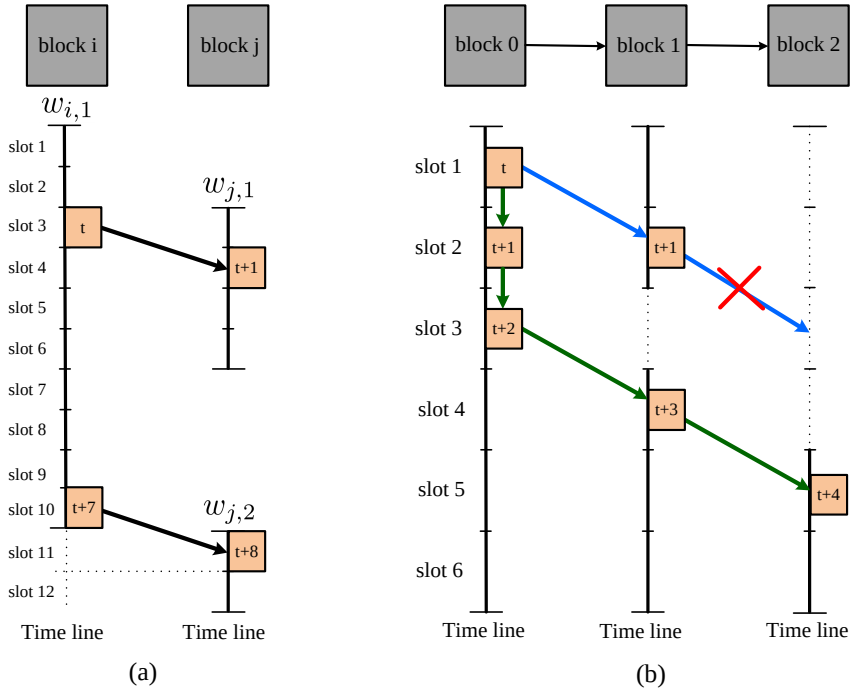

Fig. 2 (a) Reachable free time windows. (b) Example of time window search.

The dashed lines represent reserved time slots, which cannot be used in our schedule. The search fails when there is no reachable free time window to get to the next block, as shown in blue color. After waiting 2 time slots, the AGV k finds a feasible schedule-path with earliest arrival time. In this example, the schedule-path is:

$$Sch(p_k) = ((0,1),(1,4),(2,5))$$

B) Forward Time Window Searching (F-TWS)

Our forward searching algorithm is trying to get the schedule path with earliest arrival time through enumerating all combinations of reachable free time windows on the candidate path. The algorithm will always output the schedule-path once the optimum solution appears. This strategy searches from the starting block S_k with start time slot t_s. We push the tuple (S_k, t_s) to a queue, and then extend it with all its reachable free time windows on successor block in the path to make traverse in an enumerating way. We continue this process until getting to the destination block, or the queue is empty when the path is not feasible. The details of our forward searching algorithm is shown in Algorithm 3.

Algorithm 3: Forward Time Window Searching (F-TWS)

Input: Start time slot t, candidate path p_k to be scheduled
Output: Schdule-path $Sch(p_k)$

1 **Initination:** $Q \leftarrow \{(S_k, t)\}$;
2 **while** $Q \neq \varnothing$ **do**
3 $\quad i \leftarrow \arg\min_i\{t_i \mid t_i \in Q\}$; $Q \leftarrow Q \setminus \{(i, t_i)\}$;
4 $\quad$ **if** $i == D_k$ **then**
5 $\quad\quad$ **while** $i \neq S_k$ **do**
6 $\quad\quad\quad Sch(p_k) \leftarrow Sch(p_k) \cup \{(i, t_i)\}$;
7 $\quad\quad\quad (i, t_i) \leftarrow (i, t_i).parent$;
8 $\quad\quad Sch(p_k) \leftarrow Sch(p_k) \cup \{(i, t_i)\}$;
9 $\quad\quad$ **return** $Sch(p_k)$;
10 $\quad$ **else**
11 $\quad\quad$ **foreach** $w \in RFTW_{i,j}(t_i)$ **do**
12 $\quad\quad\quad (j, t_j) \leftarrow (j, max(t_i + 1, w.t^s))$;
13 $\quad\quad\quad (j, t_j).parent \leftarrow (i, t_i)$;
14 $\quad\quad\quad Q \leftarrow Q \cup \{(j, t_j)\}$;
15 **return** $infeasibility$;

In this algorithm, we first initialize the queue Q with tuple of starting block S_k with start time t on candidate path p_k for this AGV k (Line1). We make searching by iteratively push and pop reachable free time windows of the time slots in current time window (Line2∼Line14). In each loop, we pop out the tuple (b_i, t_i) with earliest entry time t_i from the queue Q (Line3). To extend the free time windows on block i, all reachable free time window of this block will be added to the Q (Line14). Before this, the entry time of each reachable time window will be calculated (Line12). We record the parent block-time pair in each searching, so that the final schedule path will be output in front-to-back order (Line4∼Line9). If no schedule path is found, we output infeasibility.

C) Re-selection Time Window Searching (RS-TWS)

Definition 4: Weak Reachable Free Time Window. For block i in time slot $t \in w_{i,m}$, the weak reachable free time windows of $w_{i,m}$ is the set of time windows belonging to $FTW_j(t)$ of successor block j on the condition that: $t + 1 \leq t^e_{j,n}$, denoted as $WRFTW_{i,j}(t)$.

Definition 5: Inconsistent Tuple. For schedule-path $Sch(p_k)$, we say a tuple(i, t_i) is inconsistent when the free time window $w_{i,m}$ which t_i belongs to ends earlier than the start time of the free time window $w_{j,n}$ which the subsequent tuple (j, t_j) locates. We have: $t^e_{i,m} + 1 < t^s_{j,n}(t_i \in w_{i,m}, t_j \in w_{j,n})$.

From the definition, it can be known that the weak reachable free time windows have lower requirements than reachable free time windows, thus we have: $RFTW_{i,j}(t) \in WRFTW_{i,j}(t)$, which means $RFTW_{i,j}(t)$ is a special case of $WRFTW_{i,j}(t)$. Fig. 3(a) is an example to show the weak reachable

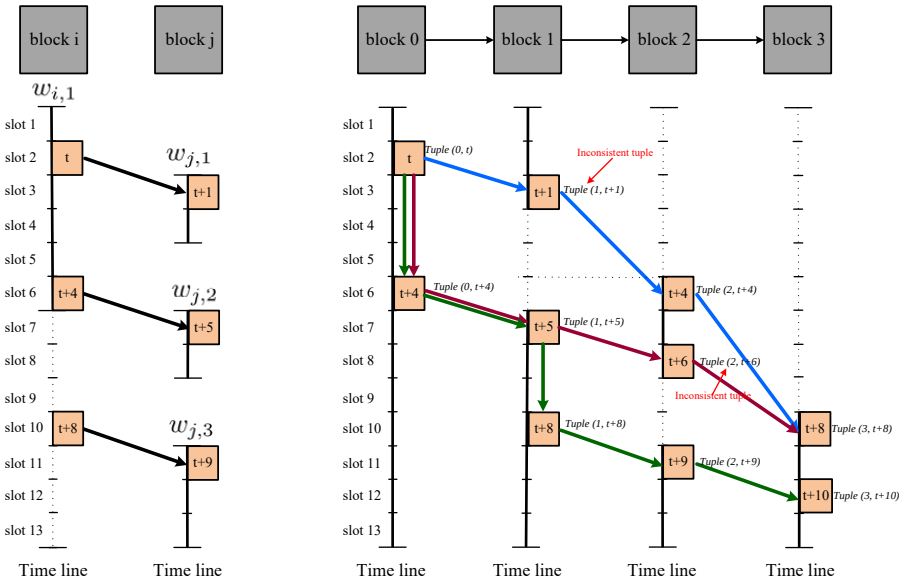

Fig. 3 (a) Weak Reachable Free Time Windows. (b) Inconsistent tuple and time window re-selection.

free time windows for block i in time slot t. In this example, there are three weak reachable free time windows on block j : $w_{j,1}$, $w_{j,2}$, $w_{j,3}$, and two of them $w_{j,1}, w_{j,2} \in RFTW_{i,j}(t)$. Another weak reachable free time windows $w_{j,3}$ though cannot be directly reached from time window $w_{i,1}$ on block i, however AGV can wait on block i ignoring other vehicles' reservation until the start time of $w_{j,3}$.

Fig. 3(b) shows how inconsistent tuple occurs. In this simple example, we get an initial schedule-path (represented by the blue arrows) by always selecting the first weak reachable free time windows to expand the schedule to the destination block. Tuple $(1, t+1)$ is an inconsistent tuple according to definition 5, because the free time window which the tuple $(2, t+4)$ locates is a weak reachable free time window of block 1, not a really reachable free time window. Thus we abandon the original free time window which inconsistent tuple $(1, t+1)$ belongs to, and re-select the next weak reachable free time window on block 1.

By introducing the concept of weak reachable free time windows, our re-selection searching algorithm carries on adjusting the schedule-path of path p_k until a feasible schedule is found or infeasibility is meet. A simple case of re-selection is also shown in Fig. 3(b). The initial schedule-path which represented by the blue arrows is not feasible for the existence of inconsistent tuple $(1, t+1)$. Then we re-select the free time window on block 1 and adjust the schedule-path all the way to the end of path. The red arrows shows the adjusted schedule-path, there is still an inconsistent tuple $(2, t+6)$, we continue the time window re-selection and schedule-path adjusting process until there

is no inconsistent tuple or the starting block is in the inconsistent tuple which means the schedule-path is infeasible. The green arrow shows the final feasible schedule-path.The details of our re-selection time window searching algorithm is shown below:

Algorithm 4: Re-selection Time Window Searching (RS-TWS)

Input: start time slot t, path p_k to be scheduled
Output: Schdule-path $Sch(p_k)$

1 $Sch(p_k) \leftarrow Sch(p_k) \cup \{(S_k, t)\}$;
2 $i \leftarrow S_k$; $j \leftarrow B_{succ}(i, p_k)$;
3 **while** $j \neq D_k$ **do**
4 $\quad (j, t_j) \leftarrow (j, max(t_i + 1, t^s_{j,n}))$; //$w_{j,n}$ is the first of $WRFTW_{i,j}(t_i)$.
5 $\quad Sch(p_k) \leftarrow Sch(p_k) \cup \{(j, t_j)\}$;
6 $\quad i \leftarrow j$; $j \leftarrow B_{succ}(j, p_k)$;
7 $(j, t_j) \leftarrow (j, max(t_i + 1, t^s_{j,n}))$;
8 $Sch(p_k) \leftarrow Sch(p_k) \cup \{(j, t_j)\}$;
9 **while** $\exists inconsistent\ tuple$ **do**
10 $\quad (j, t_j) \leftarrow$ first inconsistent tuple from $Sch(p_k)$;
11 $\quad$ **if** $j \neq S_k$ **then**
12 $\quad\quad (j, t_j) \leftarrow (j, max(t_i + 1, t^s_{j,n+1}))$; // $i \in B_{pre}(j, p_k)$, old $t_j \in w_{j,n}$, new $t_j \in w_{j,n+1}$ which follows $w_{j,n}$.
13 $\quad\quad$ **while** $B_{succ}(j, p_k) \neq D_k$ **do**
14 $\quad\quad\quad h \leftarrow B_{succ}(j, p_k)$;
15 $\quad\quad\quad (h, t_h) \leftarrow (h, max(t_j + 1, t^s_{h,m}))(w_{h,m} \in WRFTW_{j,h}(t_j))$;
16 $\quad\quad\quad j \leftarrow h$; $h \leftarrow B_{succ}(h, p_k)$;
17 $\quad\quad h \leftarrow B_{succ}(j, p_k)$; $(h, t_h) \leftarrow (h, max(t_j + 1, t^s_{h,m}))$;
18 $\quad$ **else**
19 $\quad\quad$ **return** $infeasibility$;
20 **return** $Sch(p_k)$;

In Algorithm 4, we initialize the schedule-path $Sch(p_k)$ by selecting the first weak reachable free time window on each block in the path and calculate its entry time (Line1∼line8). For the initialized $Sch(p_k)$, we check whether there exists inconsistent tuple (Line9). The schedule is feasible if no inconsistent tuple is found, then we output $Sch(p_k)$ (Line20). Otherwise, we retrieve the first inconsistent tuple (j, t_j) and check if it belongs to the start tuple in $Sch(p_k)$ (Line10). The algorithm outputs infeasibility when j is the start block S_k for the entry time of S_k is a given value t, the free time window which t belongs on the start block cannot be altered. If j belongs to other blocks on p_k, we change the entry time of block j by selecting its next weak reachable free time window and update t_j (Line12). Then start from j, we update the entry time of path blocks following j through weak reachable free time window re-selection till the end of path (Line13∼Line17).

5 Experiment

In this section, we compare our two approaches with HTN based method and TW-A* in different warehouse layout settings and different plant scales. We make evaluations of our methods using two metrics: the sorting throughput in given time period, and the number of path finding failures.

5.1 Experiment Setup

In fact, the layout of warehouse and the plant scale will greatly affect the schedule of AGVs, so that sorting throughput can be quite different under different layout settings. In this paper, we give four types of warehouse layout with scale changing from 10×10 to 64×64 blocks to validate our methods. Fig. 4 shows our layouts design with scale of 10×10 blocks, base on which we validate effectiveness of our approaches.

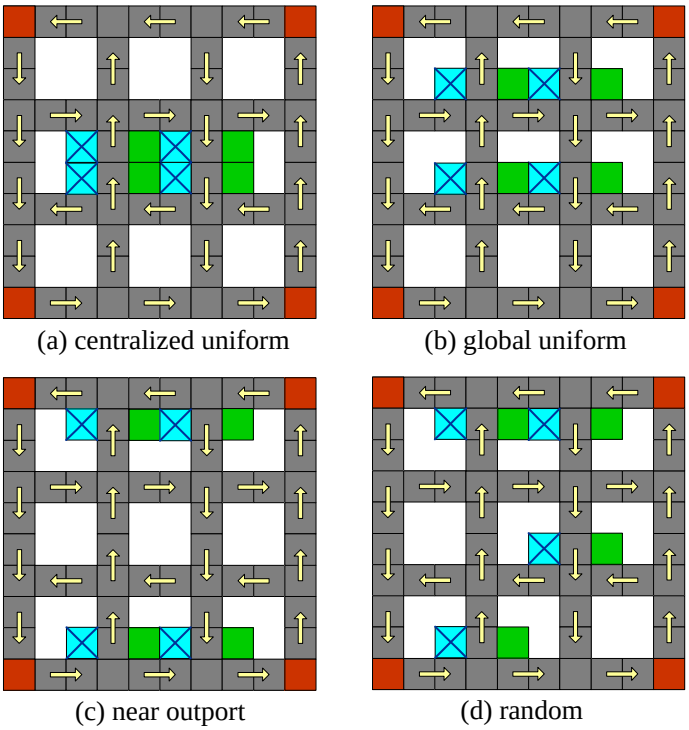

Fig. 4 Four types of warehouse layout design.

In layout (a), all sorting exports are centralized and uniformly distributed in the central part of warehouse, so that the distance from starting ports to sorting exports is basically equal. In layout (b), sorting exports are evenly distributed in the warehouse plant. For layout (c), sorting exports are set according to the principle of near starting ports. In layout (d), all sorting exports are randomly generated in the warehouse.

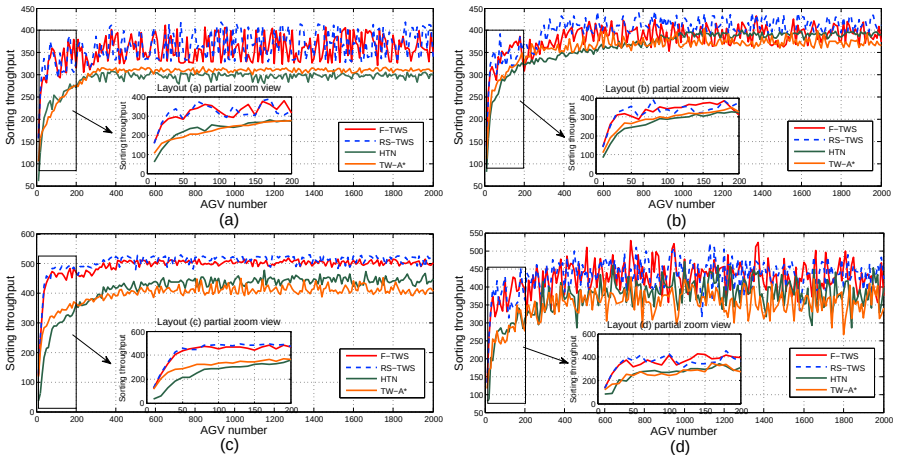

Fig. 5 The sorting throughput under various layouts.

To effectively simulate the operations of automatic sorting, we generate a set of express package sorting destinations based on real data from State Post Bureau of China [4]. Based on the statistics of the express business volume of different cities, we randomly generate the number of packages to be sent to different cities correspondingly with the same proportion.

5.2 Experiment Results

Fig. 5 shows the sorting throughput under the above four different layouts of the warehouse within given period. Generally speaking, our two algorithms outperform HTN and TW-A* no matter what the given layout is designed. It can be clearly seen that with the growing of AGV number, the sorting throughput increases correspondingly and there is an obvious gap in throughput between our algorithms and HTN, TW-A*. The zoom views in the middle give us a more clear vision of the growing trend in throughput when the number of AGVs increases from 10 to 200. From the zoom views, we can conclude that the minimum number of AGVs required to achieve maximum throughput is roughly between 50 and 60. The throughput will keep fluctuating smoothly even when the AGV number increases to 2000. It is because that the warehouse plant scale restricts the number of active AGVs, and extra vehicles can no longer be scheduled to transport more packages in limited space like this.

Fig.6 depicts the number of failures in finding valid paths. It can be seen that in each layout, our approaches perform better than existing methods with much fewer failures to find feasible paths. Our methods generate a set of candidate paths used to find the schedule-path with earliest arrival time window, decreasing the chance of failures in path searching. In each layout, the number of failures in our methods will reach a certain peak when AGV number increases to 50 or 60. When AGV number increases to a certain extent, the number of active ones will no longer increase due to the limited warehouse

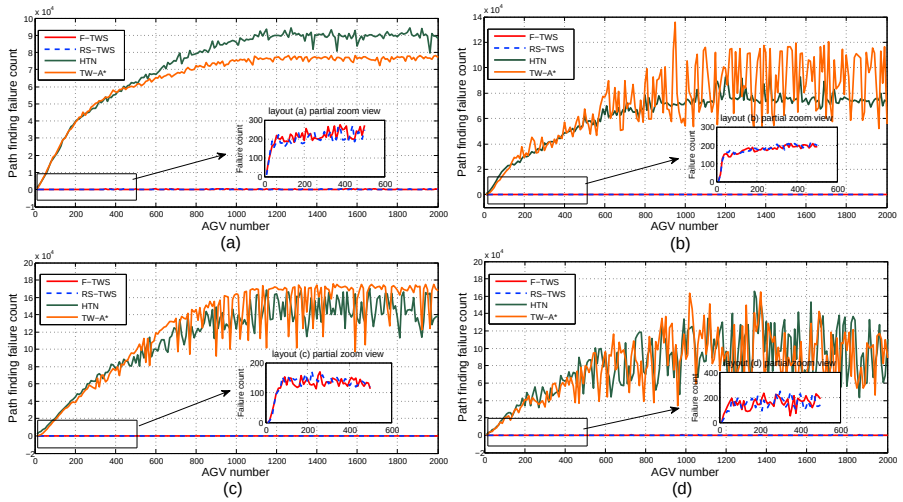

Fig. 6 The number of failures in AGV path searching.

space, so that the number of failures that are caused by active AGVs will no longer change greatly.

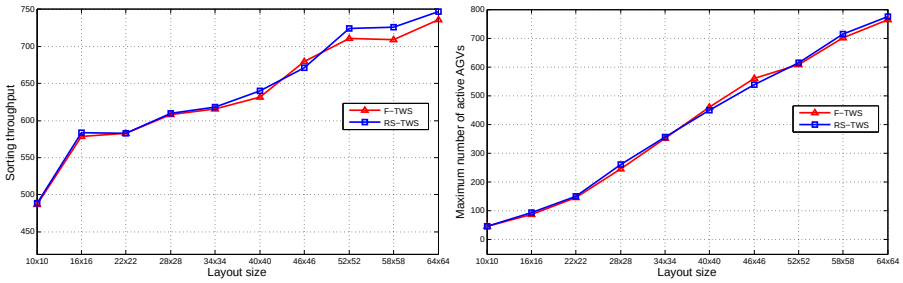

Fig. 7 (a) Throughput with plant scale. (b) Maximum number of active AGVs with plant scale.

Fig. 7(a) shows how sorting throughput changes with layout scale. In our settings, the running plant scale grows from 10×10 to 64×64 blocks, with corresponding increase of the number of starting ports and sorting exports. In this Figure, the sorting throughput increase slowly with the growing of plant scale. In larger running plant, AGVs need to travel longer distance to the sorting destinations, so that more AGVs will be scheduled to transport more packages in the same period. Fig. 7(b) shows the maximum number of active AGVs that can be accommodated in different plant scale for layout (a). It can be found that both the maximum number of active AGVs and the maximum sorting throughput are almost in linear relationship with plant scale, as can be seen in Fig. 7(a) and Fig. 7(b).

6 Conclusion

In this paper, we proposed two heurist algorithms F-TWS and RS-TWS to search for passable time windows along candidate path, so that the sorting throughput can be maximized in logistics center of express company. Compared with existing work such as HTN and TW-A*, our approaches significantly promote sorting throughput even under different layouts of warehouse plant while with less failures in path finding. With the plant scale grows, the sorting throughput and maximum number of active AGVs will increase. In future work, the problem of multi-destination path planning should be considered, in which AGVs are capable of carrying multiple express packages, and our approaches can be extended to cope with the problem in future intelligence logistics center.

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