Ants for Dynamic Job Shop Scheduling Problem: Application to Harbor Logistics*

Gaëtan Lesauvage†, Stefan Balev, Frédéric Guinand

Normandy University, LITIS EA 4108

BP 540, 76058 Le Havre, France

E-mail: {gaetan.lesauvage,stefan.balev,frederic.guinand}@litislab.eu

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Abstract

In this paper we address the problem of Dynamic Job Shop Scheduling. This problem is stemmed from a real life application occuring in Harbor Logistics. On container terminals, special vehicles, called straddle carriers, continuously move containers, from trucks/train/ships to storage areas, from storage area to ships, trucks or train or directly from a ship to another one. Moving a container in the terminal is called a mission and is considered as a job. Such a job is composed of two operations: the pickup and the delivery. Each operation takes places in a particular and fixed location. Moreover, picking up and delivering containers have to be achieved within given time windows fixed according to external constraints. The overall objective is two fold: on the one hand we want to minimize the total distance covered by the straddle carriers, and on the other hand we want to minimized non respected time windows associated to each operation. In addition, the terminal is subject to many dynamic events such as the arrival of unexpected missions, the update of some time windows, or vehicle failures for instance. For the dynamic version of the problem we have designed and implemented an ant-based approach for copping with such uncertainties, and it has been showed that our algorithm performs quite well and provides near optimal solution in reasonnable computation time.

Keywords: dynamic job shop scheduling problem, dynamic vehicle routing problem, ant colony optimization, ACO, container terminal, harbor logistics.

1 Introduction

With the development of trade activities which have continually increased, container has become the first mode of packaging for exchanging goods. One of the cheapest way to carry thousands of tons of goods around the world are containers vessels which are able to carry at once ten of thousands containers. As a consequence, multimodal platforms have been created all around the world in order to facilitate the transfer between ships and trucks or trains. In order to reduce the costs of these transferts, the harbor has to provide a high quality of service and unceasingly develop new technologies and processes. The present work focuses on one particular point of the organization of container terminals: the scheduling of straddle carriers missions.

Schematically a container terminal is divided into 5 areas : the yard composed of lanes of stacked containers, the depot where the idle vehicles are parked, the trucks area, the trais area and the quays.

Straddle carriers are used within the terminal to move containers. Those vehicles can lift a container from above and are very useful to move containers in the yard by driving over the lanes. They are also used to load or unload trucks or trains. Some of them are able to dynamically adapt the spreader size to any container dimensions while some of them require to be set up in the depot.

Each move of a container by a straddle carrier is called a mission. There are four kinds of missions:

- Incoming container missions;
- Outgoing container missions;
- Transshipment missions;
- Staying container missions.

Figure 1: The Terminal of Normandy, Le Havre's harbor, France.

The first category concerns trucks, trains and ships unloading. Straddle carriers drive to the pick-up locations and unload the vehicles, and then lift the container, drive to the yard to stock it. Concerning ships, they are unloaded by quay cranes which stack containers on the quay. Then, straddle carriers come to pick-up the containers. The second category concerns trucks, trains and ships loading. In this case, straddle carriers start by picking-up a container from the yard and then drive to the delivery location (trucks areas, trains area or ship areas) to deliver it to their recipient. The third category of missions concerns the move of a container from a ship to another one. Finally, the last kind of missions concerns internal yard optimization process. Indeed, in some cases, it can be useful to reorganize part of the stock area in order to reduce further delivery times or to free strategic container slots for next unloading missions.

Two time windows are allocated to every mission. One concerns the pickup phase, the other one is related to the delivery. These time windows are used to fix an appointment between straddle carriers and customer vehicles (trucks, trains or ships). Straddle carriers have to reach the pickup or delivery location within the given time window and so do the customers vehicles. If a straddle carrier comes too early, it will have to wait. On the contrary, if it comes too late, the customer vehicle will have to wait. As a consequence, a time window overrun implies a cost for the terminal because, if a customer has to wait excessively, it may require late fees from the container terminal exploitation company. However, in the case of yard optimization missions, the time windows can be overrun because it has no direct effect on the customers. So, according to the mission kind, time windows can be hard or soft. For incoming missions, the pickup time window is hard and the delivery time window is soft. For the outgoing container missions, the pickup time window is soft but the delivery time window is hard. For transshipment missions, both time windows are hard, and for yard optimization missions both time windows are soft.

On the terminal straddle carriers perform missions one after the other with a double objective: respecting missions time windows and minimizing the overall covered distance [2]. Indeed, time windows must be respected to avoid penalty fees and the distance covered by the vehicles directly impacts the exploitation costs of those vehicles. So, the optimization problem discussed in this paper concerns the allocation and the scheduling of the missions to the straddle carriers.

However, in real life, container terminals are subject to dynamic events occuring in an unpredictible way. For instance, new missions can be added to the system just before the beginning of their pickup time windows, some customers of the terminal may also miss the time windows making the previous computed schedule outdated. The number of straddle carriers can also change during the day if some of them broke down or are getting repaired.

All those dynamic events contribute to the uncertainty of the environment and the scheduling system must be able to cope with such events so as to provide, at any time and in any condition, feasible solutions.

Next Section presents the modeling of the problem for both static and dynamic formulations and exposes related existing works. Section 3 is devoted to the main contribution of this paper, a swarm intelligence method, based on the ant metaphor able to cope with dynamic events, for generating relevant schedules. Section 4 presents and discusses results obtained by the method on both static and dynamic versions of the problem. A final section concludes this work and opens some perspectives.

2 Problem Modeling and Related Works

In the static as well as in the dynamic version, the problem is considered for a fixed and limited period of time that will be called "day", for simplicity, in the sequel. It has to be noticed that on most containers terminals the activity is an ever-going process (24 hours a day, 7 days a week) justifying and motivating the design and implementation of resolution processes able to cope with dynamic events.

2.1 Problem Modeling

In its static version, we assume that no dynamic event can occur during the day. The number of straddle carriers is supposed to be known and fixed for the whole day. This implies that, once computed a schedule remains valid. As additional hypothesis we suppose that the travel time between two locations within the container terminal is known and does not vary during the day. Moreover we also assume that time windows are respected by the customers for either pickup or delivery. Finally all missions that are planned during the day are supposed to be known a priori.

In our context, scheduling missions for straddle carriers, the problem may be formulated as a job shop scheduling problem in which the machines are the straddle carriers and the missions are the jobs.

The problem consists in finding the schedule S of n jobs J_i $(i = 1, \ldots, n)$ on m machines M_j $(j = 1, \ldots, m)$. This schedule is represented by the workload W_{M_j} of each machine M_j. The workload W_{M_j} is an ordered list of jobs allocated to the machine M_j. Each job is made of two operations: O_1: pickup of the container and O_2: delivery of the container. As O_1 and O_2 operate on the same container, they have to be processed on the same machine (the straddle carrier) in this order. Moreover, between the execution of both operations the vehicle has to move from one place (the pickup location) to another place (the delivery location) and this movement entails a delay between O_1 and O_2 related to the distance between both locations. This problem abviously belongs to the class of the Job Shop Scheduling Problems (JSSP).

$$\begin{cases} S = \{W_1, W_2 \ldots, W_m\} & \text{and} \\ W_i = \{J_{\alpha_1}, \ldots, J_{\alpha_k}\} & \text{with } k \leq n, \text{ and } W_i \cap W_j = \emptyset, \forall i \neq j \end{cases}$$

For starting a mission, the straddle carrier has to move to the pickup location. This move can be considered as a setup time or cost. This setup time directly depends on the location of the straddle carrier at the end of the previous mission, if any. If a previous

mission was executed by the straddle carrier, then the distance used for computing the setup time is equal to the distance between the delivery location of the previous mission and the pickup location of the current one. If no mission was executed before the current one, then the straddle carrier is supposed to be located at the depot. As a consequence, setup times are sequence dependent (ST_{sd}).

Let us consider two jobs, J_i and J_j each composed of two operations, O_1^i, O_2^i and O_1^j, O_2^j. Each operation has to be performed on a precise location on the terminal. Let us denote by $l(O_p^k)$ the location of the operation p ($p \in \{1, 2\}$) of job J_k. Then, if a machine is allocated both jobs in the order J_i, J_j, then the setup cost $setup_{i,j}$ is proportional to $d(l(O_2^i), l(O_1^j))$ where $d(l, l')$ denotes the shortest path between the locations l and l'. However, if the machine performs job J_i coming from the depot, the setup is proportional to: $d(\text{depot}, l(O_1^j))$. As the machines are supposed to move at the same speed, we consider that the setup cost for chaining job J_i to job J_j on the same machine is equal to $t(d(l(O_2^i), l(O_1^j)))$.

2.1.1 Other Assumptions

In all generality, the machines may be heterogeneous, depending on their spreader size and adaptability, such that a job J_j may not be compatible with machine M_i. For instance, if the straddle carrier has a spreader only adapted to 40 feet containers, then it will not be able to process 20 feet containers missions. However, such cases have not be considered in the current work. In addition we consider that the speed of all the machines is equal.

No preemption is allowed in the straddle carrier mission scheduling problem. Preemption of a mission can only be considered during the movement phase. Indeed, both pickup and delivery are atomic operations. Thus, preempting a mission is equivalent to stopping the vehicle along the way from the pickup location to the delivery location. And stopping the mission entails an "intermediate delivery" of the container on a temporary location, followed later by picking up again the same container from that location to the final delivery one. Thus, preempting a mission can be considered as the transformation of one mission into two new missions. While such a situation is sometimes observed in real life, we assume that no mission can be split into several ones in the context of the present work.

The jobs are independent in the problem, there is no precedence constraint between them. Though, operations are constrained by time windows. So, if two jobs are scheduled successively without taking into account their time windows, those time windows can be exceeded. In the case of two missions concerning the same delivery slot in the container

terminal, if the container of the second mission must be stacked onto the container of the first mission, then the first job should be achieved before the second one. But if the second job is processed before the first one, then a new mission will be added in the pool of jobs to switch the two containers. Again, in the context of the present work, such situations are ignored.

2.1.2 Optimization criteria

Two main criteria are taken into account for optimizing the scheduling of straddle carriers missions on container terminals: the distance traveled by all the straddle carriers, and the respect of the constraints induced by jobs pickup and delivery time windows. We recall that all the machines are moving at the same speed.

The distance covered by the machines depends on both the distance between the pickup and the delivery places but also the distance between the location of the end of a job to the location of the beginning of the next executed one. Thus, for each sequence of job J_i, J_j performed by a machine, the covered distance is equal to $d(l(O_2^i), l(O_1^j))$ plus the distance $d(l(O_1^j), l(O_2^j))$. If J_i is the first job executed by the machine, then the distance is equal to $d(l(\text{depot}), l(O_1^j))$ and if the job J_j is the last job executed then an additional distance should be added to the total distance covered by the machine: $d(l(O_2^j), l(\text{depot}))$.

The second criterion is related to time windows associated to job operations. If a mission misses one or both of its time windows, then there is tardiness. Total tardiness for a job J_i allocated to machine M_k is the sum of pickup tardiness T_{i,O_1}^k and delivery tardiness T_{i,O_2}^k. The pickup tardiness is the difference between the arrival time of M_k at the pickup location of J_i and the end of the pickup time window of J_i. The delivery tardiness is the difference between the arrival time of M_k at the delivery location of J_i and the end of the delivery time window of J_i.

Let us consider that machine M_k executes the sequence J_i, J_j, and that the delivery operation of job J_i, performed by M_k, ends at C_i^k. We also denote the time needed to travelfrom location l to l', $t(d(l, l'))$ (as for the setup times). We also denote by $tw_{min}(O_1^i)$ (resp. $tw_{max}(O_2^j)$) the starting date (resp. ending date) of the time window of the pickup (resp. delivery) operation of job J_i (resp. J_j). Then, the tardiness for job J_j, executed by M_k, may be expressed as follows:

$$\begin{cases} T_{j,O_1}^k = max(0, (C_i^k + t(d(l(O_2^i), l(j, O_1)))) - tw_{max}(O_1^j)) = max(0, C_i^k + setup_{i,j} - tw_{max}(O_1^j)) \\ T_{j,O_2}^k = max(0, C_j^k - tw_{max}(O_2^j)) \\ T_j^k = T_{j,O_1}^k + T_{j,O_2}^k \end{cases}$$

The tardiness may entail some penalty costs to the container terminal. Depending on the kind of mission, these costs may be more or less important. This can be represented by weighted tardiness. For summarizing, the optimization aims at minimizing two criteria, the total distance covered by the vehicles and the total weighted tardiness.

If we consider n jobs, and if we denote $M(i)$ the machine performing job J_i, the minimization function for the tardiness can be expressed as follow:

$$F_S = min \sum_{j=1}^{n} (w_j.T_j^{M(j)})$$

and if we assume that m represents the number of machines, the workload on machine M_i is represented by $W_i = \{J_1^i, \ldots, J_k^i\}$, with $k \leq n$, and $W_i \cap W_j = \emptyset$, $\forall i \neq j$, and the schedule is: $S = \{W_1, W_2 \ldots, W_m\}$. Then, the total distance covered by a machine M_i is equal to:

$$D_i = d(l(\text{depot}), l(O_1^1)) + \sum_{k=2}^{card(W_i)} \Big(d(l(O_2^{k-1}), l(O_1^k)) + d(l(O_1^k), l(O_2^k))\Big) + d(l(O_2^{card(W_i)}), l(\text{depot}))$$

and the minimization function for the total distance covered by all the machines can be expressed as:

$$D_S = min \left(\sum_{i=1}^{m} D_i \right)$$

2.1.3 Related works

It should be noticed first that if we relax the time windows constraints, the problem may be formulated in the following terms: given a set of tasks, such that each task is composed of a pickup operation, a movement between two places (a source and a destination) and a delivery operation, how to allocate the tasks to vehicles such as to minimize the covered distance? This problem is evidently related to the class of vehicle routing problem (VRP).

Since the problem is about finding shortest routes for a fleet of vehicles, it seems natural to look at existing works dealing with Vehicle Routing Problems (VRP) [22, 12] and more precisely dealing with Pickup and Delivery Problem (PDP) [3]. This latter version of VRP consists in picking up goods before delivering them to the customers. A variant of PDP takes into account the time windows [17]. Here, the pickup and the deliveries must occur into given time intervals. There is also a version of these problems with restricted capacitate vehicles [22].

In those problems each vehicle usually has a fixed capacity greater than one and the problem is to find shortest paths to deliver the goods to the customers. In our problem, each vehicle has a unit capacity. This means that only one delivery per pickup operation is possible. Moreover, in our problem a given customer requires only one type of good, located at a given fixed place, such that no choice is possible for the pickup location and the delivery one, entailing the uselessness of routing. The only issue is related to the way the missions are chained one after the other on each vehicle, and a solution of this problem mainly depends on the pickup and delivery time windows. Thus, our problem seems to be more related with job shop scheduling than with vehicle routing.

For the Job Shop Scheduling Problem (JSSP) a set of n jobs is given as well as a set of m machines. Each Job J_i consists of a sequence of k_i operations that have to be performed in this order on different machines. Each operation is characterized by a processing time that may depend on the machine it is allocated to. In addition, a machine can process only one operation at a time and a given operation can only be processed by a single machine at a time.

In [14] and [8], the authors give a survey of Job Shop Scheduling Problems and of the methods used to solve the different sub-problems. Among the different methods used for solving the problem, an ant system algorithm has been introduced by Dorigo et al. [9]. The authors used a complete graph representing the possible schedules and tabu lists to mark the nodes (jobs) chosen by the ants. When all the jobs are in the tabu list, the solution represented by the list is evaluated by a fitness function. More recently, Apinanthana et al. extended the use of Ant Colony based algorithm to solve the Multi-criteria Job Shop Scheduling Problem [23]. In [13], the authors proposed a corresponding algorithm for the Job Shop Scheduling Problem with Time Windows (JSSP-TW). They showed that Ant Colony Optimization is both efficient and effective for this class of optimization problems.

In the Flexible Job Shop Scheduling Problem (FJSSP), all the machines are able to process any operation. This version of the Job Shop Scheduling problem has been first introduced by Brucker and Schlie in [7]. They proposed a graphical methods for solving this problem with two jobs. Since the problem is NP-Hard for more than two jobs, meta-heuristics has been used. In [20], Ponnambalam et al. introduced an Ant Colony Optimization algorithm to solve large instances of the FJSSP up to 20 jobs and 15 machines. In [24], Xing et al. used a hybrid optimization method to solve the FJSSP using both knowledge and Ant Colony Optimization models. The algorithm memorizes good features of past iterations to guide the ACO algorithm toward best solutions.

In [1] the authors give a survey of algorithms used to solve Job Shop Scheduling Problems with Sequence Dependent Setup Times (JSSP-SDST). Many different methods have been used for that problem: hybrid genetic algorithms, disjunctive graphs, mixed integer linear programming model with local search scheme, fast tabu search, branch and bound, dynamic programming, polynomial insertion algorithm, Lagrangian relaxation or ant colony algorithms. However all these methods have only been applied to a static version of the JSSP-SDST problem.

2.2 Dynamic version of the problem

In its dynamic version, the straddle carriers scheduling problem deals with dynamic events. It implies that a computed schedule can become deprecated during the day. Many different dynamic events may occur during the execution of the schedule. For instance, the travel times between each location within the container terminal, which are known a priori, may vary during the day. The number of straddle carriers, known at the beginning of the day, can change since some of them can become unavailable for whatever reason. Time windows can also be subject to some modifications if, for instance, a truck is in late for meteorological reasons. And last, but not least, some new missions may arrive at any moment of the day, without prior notice.

Some of these situations have already been studied. For instance, Berbeglia et al. described the dynamic version of pickup and delivery problems in [4]. However, in their work they do not consider time windows. This temporal constraint is present in the work of S. Mitrovic-Minic [18]. She addressed the problem of Dynamic Pickup and Delivery with Time Windows (DPDP-TW). In [19], S. Mitrovic-Minic and her colleagues used a multiple Traveler Salesman Problem (m-TSP) formulation of the Vehicle Routing Problem with Time Windows (VRP-TW). They used precedence graphs to model the multiple Traveler Salesman Problem with Time Windows (m-TSPTW). They proposed algorithms to compute bounds on the number of vehicles required to complete the deliveries. They also showed that this problem is NP-Hard.

Regarding the Job Shop Scheduling modeling of this problem, when jobs must be inserted into the computed schedule then the problem is known as the Dynamic Job Shop Scheduling Problem (DSJSSP) [21].

We propose in the next section an on-line ant colony based algorithm based able to propose near optimal solutions at any time for the problem in its dynamic version.

3 Colored Ants algorithm

Bio-inspired algorithms have been more and more used for providing solutions for hard optimization problems since the early nineties[11]. Ant-based approaches (Ant System, Ant Colony Optimisation, Ant Colony System), take advantage of some properties and characteristics that have been discovered by entomologists and sometimes have been reproduced through experiments, as it was done by Deneubourg in 1983 [10], that showed stigmergy between ants. Ant-based or stigmergic systems are particulary well adapted to dynamic optimization problems because of some of their intrinsic characteristics like: decentralized control, indirect communications (entailing positive feedback), and the evaporation of the pheromone tracks (entailing a negative feedback).

Our method relies on multiple colonies of ants. In our version, ants are attracted by pheromones of their own colony and repulsed by pheromones of foreign colonies. This mechanism results in a collaboration between the ants of a colony and a competition between the different colonies. The idea consists in making them compete for having access to jobs that are compatible, in terms of time windows.

A similar approach has been design and implemented by Bertelle et al. in [5, 6] for determining dynamically the best distribution of a parallel program on a network. They used a collaboration/competition process between colonies of artificial ants to distribute the data and the computations of a program among heterogeneous processing ressources while minimizing the communication overhead between computing and communicating ressources. The authors used a threshold to avoid ants from choosing a destination containing too much foreign pheromone and by this way the ants were implicitly balanced over the solution space. Instead of using a threshold that might be difficult to tune correctly, we will see below that we choose a linear combination of the repulsion aspect in the pseudo-random-proportional transition rule.

In our model, a colony represents a vehicle (machine). The vehicle has to choose the best sequence of missions to process, best meaning the one that both minimizes weighted tardiness and the covered distance. We modeled the different solutions as paths on a graph. The ants of the colony have to colonize the mission graph in order to find the shortest path from the source node to the sink. When an ant moves to a node, it drops pheromones according to the quality of the marked node. This pheromone will be used to guide other ants of the colony toward the node and to repulse ants of other colonies to other nodes. As each colony has the same behavior, the nodes are partitioned between

the different colonies and this distribution tends to minimize the overall covered distance of the vehicles.

Each colony is modeled by a color. In this way, each node of the graph is colored by the color of the highest amount of pheromone on this node. The solution is obtained by constructing the best paths for each color. Each path P_i of color i is built by starting at the source node and by searching among the set $S_{j,i}$ of accessible nodes colored in i the node with the highest level of pheromone. The process is repeated until either the sink node has been reached or the $S_{j,i} = \emptyset$.

3.1 Graph modeling

Let us define the directed graph $G = (V, E)$ where V is the set of vertices and E the set of edges. Each job j to schedule is modeled as a node $v_j \in V$ and the edges $e(v_j, v_k) \in V$ represent the possibility for the machines to chain up the job j with the job k.

In addition to the jobs, two other vertices are added to the graph: a source node, and a sink node. The source node is connected to each node of the graph which has an in-degree equals to zer, while the sink node is linked to each node with an out-degree equals to zero.

3.1.1 Edges

The edges are weighted to represent the cost of processing the target node mission after the source node one. The weight must take into account, on one hand, the travel time between the delivery location of the source mission and the pickup location of the target mission, and on the other hand, the potential lateness involved by chainning the two missions. In case of heterogeneous machines, Each edge should contain as many weights as there are machines in the problem, since travel times may differ from one machine to another if their speeds are different.

For the edges linking the source node to a job node, the weight is computed according to the end time of the straddle carriers current activities. If the machine is processing a job then the weight will be based on the travel time between the delivery location of the processed mission and the pickup location of the target node mission and the potential lateness on the pickup time window of the target mission. On the contrary, if the machine is idle then the weight of the edge will be the travel time between the current location of the machine and the pickup location of the target node mission and the potential lateness

based on the current time of the day.

For the edges linking the job nodes to the sink node, the weight corresponds to the travel time between the delivery location of the job and the depot.

Concerning the edges between two job nodes, the weight is the travel time between the delivery location of the origin job node and the pickup location of the target job node.

Since the travel time depends on the location and the activity of the machine, the weights are time dependent even in the static case of the problem.

The graph represents the possibilities of job scheduling for the machines. The allocation problem is next solved using colored ants colonies algorithm on this graph.

The weight $w^{(t)}(n, m, c)$ represents the travel cost of an ant of the colony c for going from node n to node m at time t. It corresponds to the weight of the edge linking n and m for the colony c. We choose to compute it as the sum between the travel time $t(n, m, c)$ between the delivery location of mission n and the pickup location of mission m for the straddle carrier c and the potential lateness $lateness^{(t)}(n, m, c)$ at time t on the pickup time window of mission m after executing mission n. F_1 and F_2 are constants used to balance the relative importance of the two criteria: travel time and lateness.

$$w^{(t)}(n, m, c) = t(n, m, c) * F_1 + lateness^{(t)}(n, m, c) * F_2$$

3.2 Dynamic graph

In the dynamic case of the problem, missions can be added, removed or updated. The graph has to allow these modifications.

When a mission is added in the jobs pool, a new node is added in the graph. It is connected by edges as described above. If the new node in the graph causes the creation of an edge to a node connected to the source node, then the edge from the source node to the other node is deleted. As well as this, if the new node insertion causes the creation of an edge to a node connected to the sink node, then the edge between the node and the sink is deleted. This process is required to force the vehicles to process all the missions. Otherwise, the best solution found by the algorithm would be not to process any job because the covered distance would be null.

A node can be removed from the graph for two reasons. On one hand, if the corresponding mission has been canceled, and on the other hand if the corresponding mission has been completed. The node is then deleted from the graph and the edges of adjacent nodes are updated according to the criteria discussed above.

When a mission is updated, the corresponding node is deleted from the graph and then re-added. This process allows to take into account the new characteristics of the mission. On the other hand, the weights of the edges are updated according to the vehicles activity.

When a vehicle starts a mission, it must complete the mission unless it broke down. In this case, the mission is updated because the pickup location may have changed if the vehicle started to move the container before broking down. Moreover, if the vehicle becomes unavailable, the ants of the corresponding colony are reseted to the source node and must remains at this node until the vehicle becomes available again. In the meantime, the evaporation process makes the previous alocation solution disapeared.

In the case where the vehicle does not broke down, it must achieve the mission. To represent this constraint in the algorithm, the ants of the colony of the vehicle starts their path finding from the current mission node. The pheromone of other colonies on this node is also evaporated to make this node totally unaccessible to the ants of other colonies.

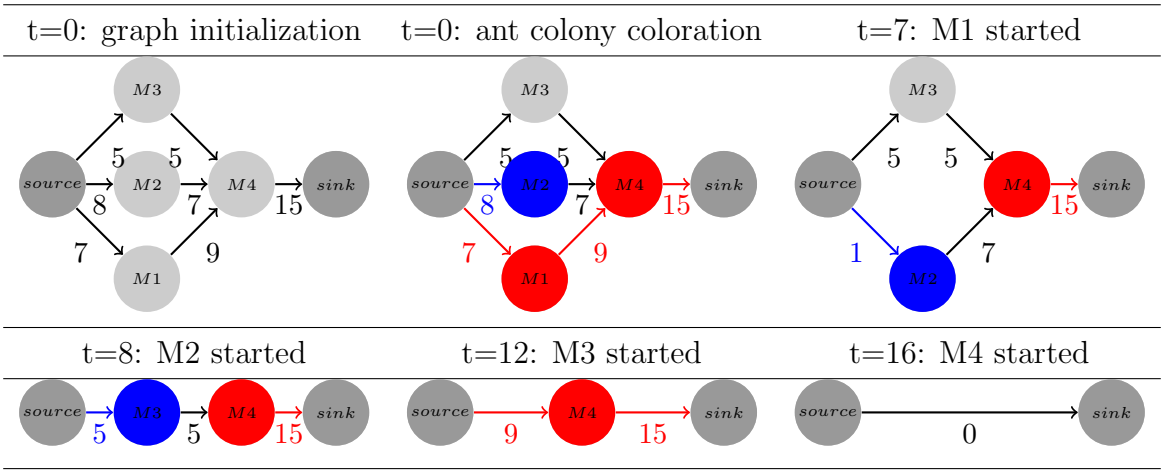

Figure 2: Dynamic graph example for 4 missions and 2 straddle carriers.

3.3 Algorithm

After each update on the graph, the following algorithm is executed Θ times.

Algorithm 2 Colored ant colony based algorithm

```
for all ant a of each colony c do
    Node destination ← choose_destination(a)
    Node n ← location(a)
    if destination = null then
        return_to_source_node()
    else
        move(a, destination)
        spread_pheromone(c, n, destination)
    end if
end for
for all node n of the mission graph do
    evaporation(n)
end for
for all colony c do
    compute_path(c)
end for
```

3.4 Pheromone handling

The quantity of pheromone of color c on the node n at time t is noted $\Omega^t(n, c)$. The quantity of pheromone of other colors than c is noted $\hat{\Omega}^{(t)}(n, c)$.

$$\hat{\Omega}^{(t)}(n, c) = \left(\sum_{k \in C} (\Omega^{(t)}(n, k)) \right) - \Omega^{(t)}(n, c)$$

3.4.1 Positive feedback

The algorithm *spread_pheromone*(Colony c, Node n, Node m) computes the quantity of pheromone $\Delta^{(t)}(m, c)$ of color c which will be dropped on the node m between the time t and $t + 1$. This quantity directly depends on the ants previous location n because it takes $w^{(t)}(n, m, c)$ into account.

$$\Delta^{(t)}(m, c) = \lambda * \frac{1}{w^{(t)}(n, m, c)}$$

3.4.2 Negative feedback

The evaporation process computes the new amount of pheromone $\tau^{(t)}(n,c)$ of color c on node n at time t as below:

$$\tau^{(t)}(n,c) = \rho\tau^{(t-1)}(n,c) + \Delta^{(t)}(n,c)$$

3.5 Pseudo-random-proportional rule

The algorithm *choose_destination*(Ant a) (see Algorithm 1) returns the destination chosen by the ant a of the colony c according to its current location node n and the probability $p^{(t)}(n,m,c)$ to choose the destination node m at time t computed by the following pseudo-random-proportional rule:

$$p^{(t)}(n,m,c) = \frac{\Omega^{(t)}(m,c)^{\alpha}\left(\frac{1}{w^{(t)}(n,m,c)}\right)^{\beta}\left(\frac{\hat{\Omega}^{(t)}(d,c)}{\sum_{k\in C}\Omega^{(t)}(m,k)}\right)^{\gamma}}{\sum_{d\in n_{out}}\left(\Omega^{(t)}(d,c)^{\alpha}\left(\frac{1}{w^{(t)}(n,d,c)}\right)^{\beta}\left(\frac{\hat{\Omega}^{(t)}(d,c)}{\sum_{k\in C}\Omega^{(t)}(d,k)}\right)^{\gamma}\right)}$$

If the chosen node m has a probability $p^{(t)}(n,m,c) < \Delta$ then the choice is refused and the ant goes back to the source node. This process is used to avoid the continous colonization of the graph by all the colonies. Indeed, if there are more vehicles than missions to allocate, then it is not possible to allocate a mission to every vehicle. Moreover, we chose to integrate the competition aspect of the algorithm in the pseudo-random-proportional transition weighted by the γ parameter.

3.6 Solutions

The schedule of each vehicle is obtained at the end of the procedure by building each best path for each color. Since the graph is directed and acyclic, the path is built by starting at the source node and by choosing from each accessible node colored by the same color that the path to build, the one with the highest quantity of pheromone. The built ends when the sink node is reached or when there is no accessible node of the color of the path.

3.7 Path reinforcement

When the first mission of a path has been started by a vehicle, a reinforcement quantity of pheromone of the color of the vehicle is spread on the whole path. This process avoid useless changes in the solution while the previous computed path is being used.

Algorithm 3 Pheromone track reinforcement of the started solution path

for all Node n in the solution S **do**

$\tau^{(t)}(n, c) = \tau^{(t-1)}(n, c) + \Lambda$

end for

3.8 Parameters

As described above, the algorithm is setted up with the following parameters:

- α: relative importance of the pheromone track in the destination choice;
- β: relative importance of the weight heuristic in the destination choice;
- γ: relative importance of the repulsion process in the destination choice;
- Δ: environment pressure rate. If the chosen destination pheromone rate is less than Δ, then the ant die (start over from the source node);
- η: number of ant per colony;
- λ: fixed quantity of pheromone spread on a destination (with $\lambda > 1$);
- Λ: quantity for reinforcement : quantity of pheromone spread on the whole path when the first mission of the path has been started;
- ρ: rate of pheromone conserved after each evaporation.

We distinguish two classes of parameters: on one hand the ones about the choice of destination for the ants (α, β, γ and Δ), and on the other hand, the ones about the pheromone handling (λ, Λ and ρ).

After testing different values for the parameter η, we decided to fix it to the number of missions in the pool. Indeed, when a mission is added, a new ant is created for each colony compatible with the mission. On the contrary, when a mission is removed from the pool, an ant is removed of each colony.

According to our simulation results, it also appears that the quality of the solution found and also the time required to find this best solution is more strongly connected to the fitness weighting the edges than to the values of the parameters. The parameters of the first class also have more influence on the quality of the solution and the convergence of the algorithm than the parameters of the second class.

4 Experiments and results

We developed an algorithm able to handle dynamics and to provide near-optimal solutions in a reasonable computation time to our problem. Since the algorithm had also to be failsafe, it ensures feasible solutions at anytime. In this section we first perform the algorithm on static versions of the scheduling problem. Then we test it on several dynamic scenarios. All of the simulations are executed on D^{2}CTS (Dynamic and Distributed Container Terminal Simulator)[16] with configuration files corresponding to the Terminal of Normandy of Le Havre's harbor. Le Havre's harbor is the biggest harbor of France in container traffic. It is located at the North West cost of France, beside the Channel, sea door between the Atlantic and the North Sea.

4.1 Measure of dynamics

In his PhD thesis[15], A. Larsen proposed two measures to determine how dynamic is an instance of a Vehicle Routing Problem. The first one is the degree of dynamism (DOD) and is calculated as the ratio between the number of dynamical requests and the total number of requests. If $dod = 0$ the problem is static, if $dod = 1$ then the problem is fully dynamic. The main weakness of this measure is that it does not take into account the arrival time of those requests. For this reason, Larsen introduced the effective degree of dynamism by the following formula:

$$edod = \frac{\sum_{i=1}^{\eta_{imm}} \left(\frac{t_i}{T}\right)}{\eta_{tot}}$$

Here η_{imm} are the requests arriving during the day which have to be planned immediately. η_{tot} corresponds to the sum of immediate requests and the requests arrived in advance. The planning horizon starts at 0 and ends at T and t_i is the time the i^{th} immediate request is recieved. This measure takes into account the average of the incoming time of the requests and gives a better appreciation of the dynamics of the scenario. Concerning the Vehicle Routing Problem with Time Windows (VRP-TW), Larsen extended the definition of *edod* by this formula:

$$edod - tw = \frac{1}{\eta_{tot}} \sum_{i=1}^{\eta_{tot}} \left(1 - \frac{r_i}{T}\right)$$

Here, r_i is the reaction time of the task i which is the difference between the latest time the request can starts and t_i which is the incoming time of the i^{th} request.

We will use *dod* and $edod - tw$ to measure the dynamics of our scenarios by setting T to the lower bound of the pickup time window of each mission.

4.2 Measure of performance

As discussed in previous sections, we want to minimize exploitation costs of the container terminal. This is the reason why we measure the performance of our algorithm by two criteria: the overall covered distance of the straddle carriers and the overspent time of the missions time windows. In addition, we also count the number overrun time windows.

4.3 Static case

To measure performance of our algorithm, we developed a Branch-and-Bound algorithm to solve the problem in the static case and to obtain optimal solutions. This algorithm is also used to solve the instances of the static problem generated from the dynamic one.

We tested here different scenarios of 5 to 12 missions with variable number of straddle carriers between 2 and 3. The small scale of the scenarios in both jobs and machines dimensions is due, of course, to the impossibility to compute optimal solutions in reasonable time. As we experiment our algorithm in the satic form of the problem $dod = 0$ and there is no dynamic events occuring during the simulations.

Missions	**Vehicles**	**Distance**		**Overspent time**		**Overrun TW**		**Execution time**	
		ACO	B&B	ACO	B&B	ACO	B&B	ACO	B&B
5	2	5073	4987	00:00:00	00:00:00	0	0	00:00:02	00:00:00
5	3	5286	4987	00:00:00	00:00:00	0	0	00:00:04	00:00:00
7	2	7807	7510	00:00:00	00:00:00	0	0	00:00:04	00:00:00
7	3	7659	7510	00:00:00	00:00:00	0	0	00:00:04	00:00:00
10	2	10207	9565	00:33:09	00:03:01	10	6	00:00:08	00:00:06
10	3	10421	9261	00:00:11	00:00:00	2	0	00:00:08	00:01:21
12	2	9336	8994	00:21:11	00:02:35	13	6	00:00:10	00:00:17
12	3	9673	9261	00:00:00	00:00:00	0	0	00:00:17	01:11:17

Concerning the static case, the results show that the ant colony algorithm provides near optimal solutions in a short computation time. However, we distinguish two kinds of algorithm behaviors according to the feasability of the scenarios. Indeed, when there is enough straddle carriers to process the missions then the ant colony algorithm provides near optimal solutions. But on the contrary, when there is not enough resources, the ant colony algorithm starts to provide lower quality solutions. This behavior shows the difficulty for the algorithm to determine how to distribute the lateness on missions.

4.4 Dynamic case

In the dynamic case, we can not have determinist algorithm to compute optimal solution since the characteristics of the problem change all along the simulation. As showed on the static results, the algorithm seems to provide a near optimal solution. With a dynamic background, the algorithm will have to adapt to the evolution of the characteristics of the problem and provide a solution at any time.

We only use dynamics on the arrival of the missions for this experiment. We tested here different scenarios of 10 to 100 missions with variable number of straddle carriers between 2 and 20. We also use different values for $edod - tw$. Indeed, the first series of experiments uses an effective degree of dynamism around 0.45. It means that each mission is known relatively early before the begining of its pickup time window.

Missions	**Vehicles**	dod	$edod - tw$	**Distance**	**Overspent T**	**Overrun TW**	**Execution t**
10	2	1.0	0.44	10217	00:12:55	6	00:00:07
10	3	1.0	0.44	8908	00:00:33	2	00:00:08
20	5	1.0	0.43	19508	00:05:15	4	00:00:44
20	7	1.0	0.43	21794	00:01:27	1	00:00:55
30	7	1.0	0.44	34458	00:06:05	3	00:01:56
30	10	1.0	0.44	35290	00:00:00	0	00:03:10
40	7	0.975	0.44	43532	00:04:52	2	00:02:48
40	10	0.975	0.44	43563	00:00:00	0	00:04:59
50	7	0.98	0.46	51855	00:46:37	19	00:05:57
50	10	0.98	0.46	51490	00:00:00	0	00:05:38
75	15	0.973	0.46	76384	00:55:00	1	00:13:43
100	20	0.98	0.46	98697	00:00:10	1	00:31:55

The second series of experiments uses the same missions than the first series but here, the missions are known at the very begining of their pickup time windows. The effective degree of dynamism is 1.0. It represents the worst case for the algorithm because it prevents it from optimizing the linking of the missions. In fact, the missions are colonized by the artificial ants and then removed from the graph. So, when other missions arrive in the schedule, they can not be linked efficiently to current missions.

Missions	**Vehicles**	dod	$edod - tw$	**Distance**	**Overspent T**	**Overrun TW**	**Execution t**
10	2	1.0	1.0	11142	00:23:29	9	00:00:04
10	3	1.0	1.0	11946	00:00:22	2	00:00:04
20	5	1.0	1.0	22177	00:08:20	7	00:00:11
20	7	1.0	1.0	25680	00:00:03	1	00:00:17
30	7	1.0	1.0	37518	00:00:00	0	00:00:20
30	10	1.0	1.0	37565	00:00:00	0	00:00:26
40	7	1.0	1.0	48275	00:00:26	3	00:00:26
40	10	1.0	1.0	49325	00:00:00	0	00:00:37
50	7	1.0	1.0	53730	00:06:11	8	00:00:38
50	10	1.0	1.0	60237	00:00:00	0	00:00:44
75	15	1.0	1.0	84178	00:00:00	0	00:01:36
100	20	1.0	1.0	108099	00:00:00	0	00:02:35

We can see with these results that the distance is not near optimal with a high effective degree of dynamism. On the contrary the time windows are mostly respected. So, the results show the robustness of the algorithm wich provide good solutions even in a unknown background.

5 Conclusions and Open Perspectives

We proposed in this paper an ant colony based algorithm to solve a real world application of the job shop scheduling problem. Indeed, the applicated problem concerns the scheduling of the missions on a straddle carrier container terminal. A container terminal is a highly dynamic environment where a lot of entities interact with each others, and its objective is to maintain a high quality of service while minimizing the exploitation costs. The theorical job shop scheduling problem associated with this application has been caracterized this way: $J|ST_{sd}, R_{sd}|\sum w_j.T_j, \sum distance(i)$.

The dynamic graph used to model the problem allows to take into account dynamic events occuring within the container terminal. Moreover, the instrinsic features of the ant colony system provide the required flexibility to adjust the proposed solutions to the changes of the environment.

Our results show that the algorithm provides, in a short computation time, near optimal solutions in low dynamic backgrounds, and proposes good solutions in higly dynamic environments.

This work can be improved by adding some of the many constraints that have been removed between the real life organization of the containers terminal and the considered model, like mission preemption, precedence relations between missions due to stacking constraints, heterogeneity, etc.

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