Space and Space-Time Organization Model for the Dynamic VRPTW

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ABSTRACT

In this paper, we present a multiagent model for the Dynamic Vehicle Routing Problem with Time Windows. The system adapts insertion methods to a distributed configuration. The model has two declination: one spatial and one spatiotemporal. The two organization models that we propose rely on two different measures of what the insertion of the current customer would cost to a given vehicle. Our approach provides promising results and provides a new method to tackle the problem, in which the solving process is future-centered. The models developed in this paper offer two solutions with different advantages, which allow a decider to choose one of them following the operational configuration of her real problem. In the case where the transportation operator has a limited vehicles fleet, and where the mobilization of a new vehicle is costly, its system should be grounded on the spatiotemporal model, which mobilizes less vehicles. In contrast, if the costs in term of traveled distance are more critical, it is more interesting to ground its system on the spatial model.

Keywords

Organization, Multiagent Systems, Routing.

1. INTRODUCTION

Several operational distribution problems, such as the deliveries of goods to stores, the routing of school buses, the distribution of newspapers and mail etc. are instantiations of NP-Hard theoretical problems called the Vehicle Routing Problems (VRP). In its original version, a VRP is a multivehicle Traveling Salesman Problem: there exists a certain number of nodes to be visited once by a limited number of vehicles. The objective is to find a set of vehicles' routes that minimizes the total distance traveled. Besides their practical usefulness, the VRP and its extensions are challenging optimization problems with an academic stimulating issues. One of the most widely studied variant of the problem is the time (and capacity) constrained version: the Vehicle Routing Problem with Time Windows (VRPTW henceforth), in which the requests to be handled are not simply nodes, but customers. For each customer, the following information are informed: the concerned node, two temporal bounds between which he desires to be visited and a quantity (number

of goods to receive, number of persons to transport, etc.). Each vehicle has a limited capacity, which should not be exceeded by the quantities that it transports. The addition of time windows increases the complexity of the problem, since it narrows the space of valid solutions. The VRPTW can be formally stated as follows.

Let G = (V, E) be a graph with node set $V = N \cup 0$ and edge set $E = (ij)|i \in V, j \in V, i \neq j, N = 1, 2..., n$ is the customer set with node 0 is the depot. With each node $i \in V$ is associated a customer demand $q_i(q_0 = 0)$, a service time $s_i(s_0 = 0)$, and a hard service-time window $[e_i, l_i]$ i.e. a vehicle must be at *i* before l_i but can be at *i* before e_i and must wait until the service starts. For every edge $(i, j) \in A$, a distance $d_{ij} \geq 0$ and a travel time $t_{ij} \geq 0$ are given. Moreover, the fleet of vehicles is homogeneous and every vehicle is initially located and end its route at a central depot. Each customer demand is assumed to be less than the vehicle capacity *Cap*. The objective is to find an optimal set of routes (with the minimal cost) such that:

- 1. All routes start and end at the depot;
- 2. each customer in N is visited exactly once within its time window;
- 3. the total of customer demands for each route cannot exceed the vehicle capacity *Cap*.

The performance criteria are in general (following this order):

- 1. The number of vehicles used,
- 2. the total distance traveled,
- 3. the total waiting time.

Since the problem is NP-hard, exact approaches are only of theoretical interest, and heuristics are performed in order to find good solutions, not necessarily optimal, within reasonable computational times. The VRP and the VRPTW can be divided into two sets [18]: static problems and dynamic problems. The distinction between these two categories relies traditionally on the knowledge (static problem) or the ignorance (dynamic problem) before the start of the solving process of all the customers that have to be visited. The operational problems are rarely fully static and we can reasonably say that today a static system cannot meet the mobility needs of the users. Indeed, operational vehicle routing problems are rarely fully static. In operational settings, and even if the whole number of customers to be served is known, there is still some elements that makes the problem dynamic. These elements include breakdowns, delays, noshows, etc. It is thus always useful to consider a problem that is not fully static.

We rely on the multiagent paradigm for solving the dynamic VRPTW. An agent is a software system, that is situated in some environment and that is able to apply autonomous actions to satisfy its goals [27], and a MAS is a network of loosely coupled agents, which interact to solve problems that overpass the capacities or the knowledges of each one [25]. A multiagent modeling of the dynamic VRPTW is relevant for the following reasons. First, since it's a hard problem, choosing a design allowing for the distribution of computation can be a solution to propose short answer times to customers requests. Second, with the technological developments, it is reasonable to consider vehicles with onboard calculation capabilities. In this context, the problem is, defacto, distributed and necessitates an adapted modeling to take profit of the onboard equipments of the vehicles. Finally, the consideration of a multiagent point of view allows to envision new measures, new heuristics, not envisaged by centralized approaches.

In this paper, we propose a distributed version of the "insertion heuristics". Insertion heuristics is a method which consists in inserting the customers following their appearance order in the routes of the vehicles. The vehicle chosen to insert the considered customer is the one that has to make the minimal detour to visit him. Several multiagent works in the literature have been proposed to distribute insertion heuristics, but very few propose new measures of the insertion cost of a customer in the route of a vehicle, as an alternative to the traditional measure of its incurred detour. In the present work, we do propose two new measures, in the context of two new self-organization models. They are based on a space and on a space-time representation of the Vehicle agents' action zones. The objective is to allow the MAS to self-adapt exhibiting an equilibrated distribution of his Vehicle agents, and to decrease this way the number of vehicles mobilized to serve the customers.

The remainder of this paper is structured as follows. In section 2, we discuss previous proposals for the dynamic VRPTW w.r.t our approach. In the sections 3 and 4, we detail the two models and the use of new measures for the insertion decisions of the vehicles.We report on our experimental results in Section 6 and then Conclude with a few remarks.

2. RELATED WORK

As we said in the introduction, exact approaches cannot meet operational settings, and upon the relatively small set of benchmarking problems of [24] - 56 problems of 100 Euclidean customers¹ each, only 45 have a known optimal solution up until today [21]. However, interested readers of optimization approaches can refer to, e.g. [16] for a survey.

In fact, most of the proposed solution methods are heuristic or metaheuristic methods, provide good results in nonexponential times, and which have presented good results with benchmark problems. For instance, large-neighborhood local search [1, 22], iterative local search [15, 14], multi-start local search [19], simulated annealing [2], evolutive strategies [20, 11] and ant colonies [7]. These approaches present the best performances with static problems (where the set of transport requests is known *a priori*). For an extensive survey of the literature for the VRPTW approaches, the reader is invited to refer to, e.g. [10, 3].

Generally speaking, most of the works dealing with the dynamic VRPTW are more or less direct adaptations of static methods. For instance, the large-neighborhood local search is adapted to a dynamic context in [8]. In [13], the authors propose to adapt the genetic algorithms to deal with the dynamic VRPTW. The proposed algorithm starts by creating a population of initial solutions and tries continually to improve their quality. When a new customer reveals, he is inserted in all current solutions in the position minimizing the additional cost. Upon the static methods, insertion heuristics are the most widely adapted in a dynamic environment (e.g. [6, 12, 4]). Insertion heuristics are, in their original version, greedy algorithms, in the sense that the decision to insert a given customer in the route of a vehicle is irrevocable. They are also combined with meta-heuristics to improve the quality of the solutions. In [30], the authors propose an approach for the dynamic VRP, in which a central solver made of reactors manage the events coming up in the network. When a customer reveals, he is inserted in the route of a vehicle as for insertion heuristics. After each insertion, an optimization procedure is launched trying to reduce the number of used vehicles and the total traveled distance. The procedure is repeated until the current solution doesn't get better anymore. The customers are handled sequentially following a decreasing priority order, which is function of their respective distance and the decreasing order of their opening time windows.

The advantage of using insertion heuristics is that they are intuitive and fast. However, when they are applied in a dynamic context, their solving process is said to be myopic. Indeed, the system doesn't know which customers will appear once it has assigned the known customers to the vehicles. And even if we could have an optimal assignment and scheduling of the known customers, a new coming customer could make the old assignment sub-optimal, which would in the worst case - necessitate a whole recomputation of all the routes.

Most of the multiagent approaches for the dynamic VRPTW are grounded, at least partially, on insertion heuristics. In [26] and in [17], the authors propose a multiagent architecture to solve a VRP and a multi-depot VRP for the first and a dial-a-ride problem for the second. The principle is the same: distribute an insertion heuristic, followed by a postoptimization step. In [26], the customers are handled sequentially, broadcasted to all the vehicles, which in turn propose insertion offers and the best proposal is retained by the customer. In the second step, the vehicles exchange customers to improve their solutions, each vehicle knowing the other agents of the system. Since vehicles are running in parallel, the authors envision to apply different heuristics for each vehicle, without changing the architecture. In-Time [17] is a system composed of *Customer* agents and Vehicle agents. The Customer agent announces himself and all the Vehicle agents calculate his insertion cost in their

¹Euclidean customers have cartesian coordinates, and the distance and the le travel times between each pair of customers are calculated following the Euclidean metric.

routes. Again, the *Customer* agent selects the cheapest offer. The authors propose a distributed local search method to improve the solutions. Indeed, they allow a customer to ask stochastically to cancel his current assignment and to de reannounce himself to the system, with the objective of having a better deal with another vehicle. MARS [5] models a cooperative scheduling in a maritime shipping company in the form of a multiagent system. The solution to the global scheduling problem emerges from the local decisions. The system uses an extension of the Contract Net Protocol (CNP) [23] and shows that it can be used for having good initial solutions to complex problems of tasks assignment. The MAS profits from an *a priori* structuring of the agents, since each vehicle is associated with a particular society and can handle the only customers of this society.

From a protocol and an architecture point of view, our system sticks with the systems we have just described, since we propose a distributed version of insertion heuristics. However, in these proposals, none have focused on the redefinition of the insertion cost of a customer. The traditional insertion cost of a customer in the route of a vehicle is based on the incurred detour of the vehicle. We propose a new insertion cost measure, focused on the space-time coverage of the vehicles, which aims at counterbalancing the myopia of the traditional measures, by privileging an insertion process that is future-centered.

3. SPATIAL MODEL

The optimization of the conventional criteria of the VRPTW (number of vehicles and total distance) leads to the appearance of uncovered areas because of their low density. In fact, the fact that we deal with a dynamic and nondeterministic problem can lead to the appearance of two different but non independent phenomena. The first is the concentration of vehicles in some zones which are more attractive and may lead to the second phenomena, which is the lack of service elsewhere. The idea behind our self-organization models is that when the positioning of vehicles is made such as to cover as much territory as possible, the risk of customers whose demand is unsatisfied, and the obligation to mobilize new vehicles to serve them, decreases. The choices we make to solve this problem is to use the multiagent paradigm coupled with the insertion heuristics. In this context, we have only one lever to change the system's behavior, which is the way in which the Vehicle agents calculate the insertion cost of a customer. These calculation methods are two dimensional: spatial and spatiotemporal. The two self-organization models that we propose have the objective of minimizing the number of used vehicles, while keeping the use of a "pure" insertion heuristics, i.e. without any further improvements or post-optimization.

Our systems are composed of a dynamic set of agents which interact to solve the dynamic VRPTW. A solution consists of a series of vehicles routes, each route consists of a sequence of customers with their associated visit time. We define two categories of agents. *Customer* agents, which represent users of the system (persons or goods) and *Vehicle* agents. We assume that there is an access point to the system (Web server, GUI, simulator, etc.) which verifies the correctness of customers requests (existing node, valid time windows, etc.) before to create the corresponding *Customer* agents. Once created, a *Customer* agent announces itself to all the *Vehicle* agents of the MAS. Each *Vehicle* agent sends an offer to the *Customer* agent with a corresponding insertion cost. The *Customer* agent chooses the *Vehicle* agent with the lower cost. Finally, the chosen *Vehicle* agent inserts the customer in its route.

Following the description above, the *Customer* agent chooses between several Vehicle agents the one with the minimal proposed insertion cost. The systems that are based on this heuristic use generally the measure of Solomon [24] as an insertion cost. This measure consists in inserting the customer which has the minimal impact on the general cost of the vehicle (which is generally function of the vehicle's incurred detour). This measure is simple and the most intuitive but has a serious drawback, since inserting the current customer might make lots of future customers' insertions infeasible, with the current number of vehicles. Its problem is that it generates vehicles' plans that are very constrained in time and space, i.e. plans that offer a few possibilities of insertion between each pair of adjacent planned customers. As a consequence, the appearance of new customers might oblige the system to create new vehicles to serve them. Through the modeling of Vehicle agents' action zones, we propose a new way to compute the customer's insertion cost in the route of a vehicle, and a new choice criterion between vehicles for the insertion of a given customer. We propose a new method that allows the system to choose the Vehicle agent "which decrease in the probability to participate in future insertions is minimal", to serve the new customer. The logic of our models is different from the traditional models, which focus on the increase of the traveled distance, neglecting the impact of the current insertion decision on future insertion possibilities.

The objective of the spatial self-organization model is to allow the specialization of the system's vehicle to zones while maintaining an optimal coverage of the network (cf.Figure 1). Thus, we define action zones on the transportation network, to which the vehicles are attached. The attachment of vehicles to their zones is not encoded in the vehicle behavior, but it has an effect on how they calculate their customers insertion costs. This computation should ensure that a *Vehicle* agent plans its route so that it's incentive to stay in its zone. The definition of geographical zones of vehicles is treated as a partitioning graph problem and is left out of the scope of this paper. We suppose that the definition of these zones is a system parameter, which is the responsibility of an expert. Each zone is defined by a set of nodes and a barycentre.

DEFINITION 1. Spatial Action Zone

Let G = (N, A) be a graph with a set of nodes $N = \{(n_i)\}, i = \{0, \ldots, m\}$ (node n_0 is the depot) and a set of arcs $A = \{(n_i, n_j) | n_i \in N, n_j \in N, n_i \neq n_j\}$. Let the costs matrix $C = \{(C_{ij})\}$ of size $m \times m$ (the arc (n_i, n_j) has a distance of C_{ij}). We define the zone $\zeta = (N_{\zeta}, A_{\zeta})$ as a subgraph of G.

DEFINITION 2. barycentre of a Zone

The barycentre of zone ζ is a node $n^{*\zeta}$ of N_{ζ} that minimize $\sum_{y \in N_{\zeta}} d_{n^{*\zeta},y}$.

Each zone is defined by a barycentre and a set of nodes (cf.Figure 2). The barycentre of a zone corresponds to the node which is the closest to all other nodes in the zone. At any point in time, each *Vehicle* agent has a distance from its action zone. This distance depends the customers inserted into its route. It is computed such as to include a penalty β



Figure 1: Specialization and Attraction Zones



Figure 2: Spatial Action Zones

to the *Vehicle* agent distance if it integrates nodes outside its zone. Indeed, if the node is inside the vehicle's zone, its distance from the barycentre of the action zone remains unchanged. Otherwise, its distance is multiplied by a factor β which is a system parameter.

DEFINITION 3. Vehicle Distance from its Zone

The distance of a vehicle v from its zone ζ_v at a given moment is equal to the average distance of the nodes in its route from the barycentre of ζ_v :

$$d_{v,\zeta_v} = \frac{\sum_{n^v \in Nodes(v)} d_{n^v, n^*\zeta}}{card(Nodes(v))}$$

with

$$\forall c \in N, d_{n^{v},c} = \begin{cases} d_{n^{v},c} & \text{if } n^{v} \in z_{v} \\ \beta \times d_{n^{v},c} & \text{else} \end{cases}$$

Nodes(v) represents the nodes of the Vehicle agent's route and card(Nodes(v)) is the number of nodes in Nodes(v). Finally, β is the penalty imposed to the vehicle distance, if its route integrates nodes which are outside v's zone.

The offer that a *Vehicle* agent proposes to a customer for its insertion is equal to the old distance of the vehicle from its zone minus its new one, if it had to insert the customer. The bigger β is, the more the vehicles are organized so that they stay in their zones. The definition of geographical zones of vehicles is treated as a partitioning graph problem and is left out of the scope of this paper. We suppose that the definition of these zones is a system parameter, which is the responsibility of an expert.

4. SPATIOTEMPORAL MODEL

Even if it allows a better spatial coverage of the network, the spatial self-organization model has two major drawbacks. First, it assumes *a priori* geographical segmentation. With the absence of data on previous customers demands, this task requires a great calibration effort to specify the most efficient zones' segmentation. Second, it doesn't incorporate the temporal dimension of the problem, since a vehicle might not be able to serve a customer even if it is located in its zone, because of the time constraints. In the following, we propose to integrate the temporal dimension in the *Vehicle* agents' action zones and to eliminate any *a priori* definition of these zones.

In the heuristics and multiagent methods of the literature, the hierarchical objective of minimizing the number of mobilized vehicles is considered in priority w.r.t the distance traveled by all the vehicles. The vast majority of the literature heuristics are as a consequence based on a two-phase approach: the minimization of the number of vehicles, followed by the minimization of the traveled distance [21]. The model that we propose in this section has the objective of minimizing the number of used vehicles, while keeping the use of a "pure" insertion heuristics, i.e. without any further improvements.

To this end, our model allows Vehicle agents to cover a maximal space-time zone of the transportation network, avoiding this way the mobilization of a new vehicle if a new customer appears in an uncovered zone [28]. A space-time pair $\langle i, t \rangle$ - with *i* a node and *t* a time - is said to be "covered" by a Vehicle agent *v* if *v* can be in *i* at *t*. In the context of the dynamic VRPTW, maximizing the space-time coverage of Vehicle agents results in giving the maximum chance to satisfy the demand of a future (unknown) customer. The logic of this measure is different from the traditional measures', which focus on the increase of the traveled distance, neglecting the impact of the current insertion decision on future insertion possibilities.

Following the description of the previous section, the Dispatcher agent chooses between several Vehicle agents the one with the minimal proposed insertion cost. The systems that are based on this heuristic use generally the measure of Solomon [24] as an insertion cost. This measure consists in inserting the customer which has the minimal impact on the general cost of the vehicle (which is generally function of the vehicle's incurred detour). This measure is simple and the most intuitive but has a serious drawback, since the insertion of the current customer might result in making the insertion of a great number of future customers infeasible, with the current number of vehicles. Its problem is that it generates vehicles' plans that are very constrained in time and space, i.e. plans that offer a few possibilities of insertion between each pair of adjacent planned customers. As a consequence, the appearance of new customers risks to oblige the system to create a new vehicle to serve them. Through the modeling of Vehicle agents' Action Zones, we propose a new way to compute the customer's insertion cost in the route of a vehicle, and a new choice criterion between vehicles for the insertion of a given customer. We propose a computation which objective is to choose, provided a new-comer customer, the *Vehicle* agent "which decrease in the probability to participate in future insertions is minimal". We use that variation of *Vehicle* agents' Action Zone as an insertion cost for the insertion of a given customer in its route.

4.1 Environment Modeling

The space-time Action Zone of a Vehicle agent is composed of a subset of the network nodes, together with the times that are associated to them. We model the MAS environment in the form of a space-time network, inferred from the network graph. Each node of the graph becomes a pair $\langle space, time \rangle$, which represents the "state" of the node in a discrete time period. The space-time network is composed of several subgraphs, where each subgraph is a copy of the static graph, and corresponds to the state of the graph in a certain period of time (cf. Figure 3). We index the nodes of a subgraph as follows: $(0, t), \ldots, (N, t)$, with $t \in \{1, \ldots, h\}$, with $0, \ldots, N$ are the nodes of the network and h the number of considered discrete periods. The total number of nodes in the space-time network is equal to $h \times N$. The edges linking the nodes of a subgraph are those of the static graph, and the costs are the travel times as described in the introduction $(t_{ij}).$



Figure 3: Space-Time Network

4.2 Intuition of the Action Zones



Figure 4: Feasible insertion

Consider a Vehicle agent v that has an empty route. In order for this agent to be able to insert a new customer c described by: n a node, [e, l] a time window, s a service time, and q a quantity - l has to be big enough to allow v to be in n without violating his time constraints. More precisely, the current time t, plus the travel time between the depot and n has to be less or equal to l (cf. Figure 4). Starting from this observation, we define the Action Zone of a Vehicle agent as the potential customers that satisfy this constraint. To do so, we define the Action Zone of a Vehicle agent as the set of pairs $\langle n, t \rangle$ of the space-time network that remain valid given his current route (n can be visited by the vehicle at t). The Action Zone of a Vehicle agent with an empty route is illustrated by the triangular shadow in the Figure 5 (it is actually a conic shadow in a three-dimensional space).



Figure 5: Initial Space-Time Action Zone

When a Vehicle agent inserts a customer in his route, his Action Zone is recomputed, since some $\langle node, time \rangle$ pairs become not valid because of his insertion. In the Figure 6, a new customer is inserted in the route of the vehicle. The Action Zone of the Vehicle agent after inserting the customer is represented by the interior of the contour of the bold lines, which represent the space-time nodes which remain accessible after the insertion of the customer (the computation of the new Action Zone is explained later).

The associated cost to an offer from a *Vehicle* agent v for the insertion of a *Customer* agent c corresponds to the hypothetical decrease of the Action Zone of v following the insertion of c in his route.

The idea is that the chosen *Vehicle* for the insertion of a customer is the one that looses the minimal chance to be candidate for the insertion of future customers. Thus, the criterion that is maximized by the society of *Vehicle* agents is the sum of their Action Zones, i.e. the capacity that the MAS has to react to the appearance of *Customer* agents, without mobilizing new vehicles.

To illustrate the Action Zones and their dynamics, we present the version of the measure that is related to an Euclidean problem, i.e. where travel times are computed following the Euclidean metric. The following paragraphs detail the measure as well as its dynamics.

4.3 The Computation of Action Zones

In the Euclidean case, the transportation network is a



Figure 6: Action Zone after the Insertion of a Customer

plane, and the travel times between two points i (described by (x_i, y_i)) and j (described by (x_j, y_j)) is equal to

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

Therefore, if a vehicle is in *i* at the moment *t*, he cannot be in *j* earlier than $t_i + \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. We can compute at any time, from the current position

We can compute at any time, from the current position of a vehicle, the set of triples (x, y, t) where he can be in the future. Indeed, considering a plane with an X-axis in $[x_{min}, x_{max}]$ and a Y-axis in $[y_{min}, y_{max}]$, the set of spacetime positions is the set of points in the cube delimited by $[x_{min}, x_{max}], [y_{min}, y_{max}]$ and $[e_0, l_0]$ (recall that e_0 and l_0 are the scheduling horizon and are the minimal and maximal values for the time windows). Consider a vehicle in the depot (x_0, y_0) at t_0 . The set of points (x, y, t) that are accessible by this vehicle are described by the following inequality:

$$\sqrt{(x-x_0)^2 + (y-y_0)^2} \le (t-t_0)$$

The (x, y, t) satisfying this inequality are those that are positioned inside the cone C of vertex (x_0, y_0, t_0) and with the equation $\sqrt{(x-x_0)^2 + (y-y_0)^2} = (t-t_0)$ (c.f Figure 7). This cone represents the Action Zone of a Vehicle agent,



Figure 7: Initial Action Zone

with an empty route, in the Euclidean case. It represents all the possible space-time positions that this *Vehicle* agent is able to have in the future. We use the Action Zone of the *Vehicle* agents when a *Customer* agent has to choose between several *Vehicle* agents for his insertion. We have to be able to compare the Action Zones of different *Vehicle* agents. To do so, we propose to quantify it, by computing the volume of the cone C representing the future possible positions of the vehicle:

$$Volume(\mathcal{C}) = \frac{1}{3} \times \pi \times (l_0 - e_0)^3$$

This is the quantification of the initial Action Zone of any new *Vehicle* agent joining the MAS. When a new *Customer* agent appears, a *Vehicle* agent computes his new Action Zone, the cost that he proposes to the *Dispatcher* agent is the difference between his old Action Zone and his new one. The new Action Zone computation is detailed in the following paragraph.

4.4 Dynamics of the Action Zones

Consider a customer c_2 (of coordinates (x_2, y_2) and with a time window $[e_2, l_2]$) that joins the system, and suppose that v is temporarily the only available *Vehicle* agent of the system and has an empty route. The agent v has to deduce his new space-time action zone, i.e. the space-time nodes that he can still reach without violating the time constraints of c_2 . The new action zone answers the following questions: "if v had to be in (x_2, y_2) at l_2 , where would he have been before? And if he had to be there at e_2 where would he be after $e_2 + s_2$?". The triples (x, y, t) where the *Vehicle* agent can be before visiting c_2 are described by the inequality [a], and the triples (x, y, t) where he can be after visiting c_2 are describe by the inequality [b].

$$\sqrt{(x-x_2)^2 + (y-y_2)^2} \le (l_2 - (t)) \qquad [a]$$

$$\sqrt{(x-x_2)^2 + (y-y_2)^2} \le (t - (e_2 + s_2)) \qquad [b]$$

The new Action Zone is illustrated by the Figure 8: the new measure consists in the intersection of the initial cone C with the union of the two new cones described by the inequalities [a] and [b] (denoted respectively by C_1 and C_2). The new measure of the Action Zone is equal to the volume of the intersection of C with the union of C_1 and C_2 . The complete computation of the volume of the intersection of these two cones is reported in the Appendix A of [29].



Figure 8: Space-Time Action Zone after the insertion of c_2

The cost of the insertion of a customer in the route of a vehicle is equal to the measure associated with the old Action Zone of the vehicle minus the measure of the new Action Zone, after the insertion of the customer. The quantity measured represents the space-time positions that the vehicle cannot have anymore, if he had to insert this customer in his route. The retained *Vehicle* agent to visit a given customer is the one for which the insertion of the customer causes less loss in his space-time Action Zone. This corresponds to choosing the vehicle that looses the minimal possibilities to be candidate for future customers.

4.5 Coordination of Action Zones

The objective of the self-organization model is to allow a better space and space-time coverage of the transportation network. This improvement is materialized by a minimal mobilization of vehicles in front of the appearance of new customers. With the mechanism described until now, every Vehicle agent tries to maximize its own action zone independently from the other agents of the MAS. However, it would be more interesting to incite the agents society in its whole to cover the network in the most efficient way. More precisely, the fact that a vehicle loses space-time nodes that it is the only one to cover should be more costly than to lose nodes that are covered by other agents.

To this end, to every node of the space-time network, we start by associating the list of vehicles covering it. Then, to every creation of a new vehicle agent, the set of space-time nodes that are part of its action zone is computed. The vehicle proceeds then with the notification of these nodes that they are part of its action zone. ces nœuds qu'ils font partie de sa *zone d'action*. Every node updates its list of vehicles that are covering it at each notification from a Vehicle agent. Similarly, when the action zone of a Vehicle agent loses a node, the node is notified and its vehicles list updated.

Now, when the insertion cost of a customer is computed, avery Vehicle agent starts by calculating the space-time nodes that it would lose if it happens to insert the new customer. Then, it interrogates each of these nodes about the "price to pay" if it happens to not cover them anymore. This price is inversely proportional to the number of vehicles covering this node. More precisely, the price to pay is equal to

$$\frac{1}{card(v_{\langle n,t\rangle})}$$

with $v_{\langle n,t\rangle}$ denoting the Vehicle agents covering the spacetime node $\langle n,t\rangle$.

This way, the space-time network being the only entity knowing the action zones of all the Vehicle agents (thanks to the lists of vehicles associated with the nodes), it associates more or less penalty to the decisions of non-coverage of the network by the vehicles as time progresses. Thus, the Vehicle agents are incited to cover the whole network in a coordinated way, improving by doing so the reactivity of the MAS.

5. SIMULATION TOOL

In this section, we briefly introduce the tool that we propose for the scenarios simulation of the dynamic VRPTW. Except for dedicated projects and commercial applications, the systems proposing a platform for the simulation of vehicle routing systems are rare. We choose to develop such an application for several reasons. First, this allows us to have a pragmatic vision of the execution environment of our proposals. Then, such an application inists on the finality of our proposals, which is to develop a decision support system for transport operators. As will be illustrated hereafter, the operator is offered an interface with the state of its fleet and the ongoing customers. These indicators allow her to perform some afjustments when needed. Eventually, the operator will have the possibility to choose between the three models that we propose the most suitable one, provided her operational settings. Finally, a Web application is also proposed for the customers, to demonstrate the deployment scenario that we envision for our system, from the customer's viewpoint. Here follow some screenshots of the simulation tool.



Figure 9: Vehicle Plans



Figure 10: Customers' Itinerary

6. **RESULTS**

Marius M. Solomon [24] has created a set of different static problems for the VRPTW. It is now admitted that these problems are challenging and diverse enough to compare with enough confidence the different proposed methods. A proof for that claim is that there is no unique heuristic that provides the best results for each one of these problems at the same time. In Solomon's benchmarks, six different



Figure 11: Booking Form

	Δ Distance		Δ Space-Time		Δ Space	
Problem	Fleet	Dist	Fleet	Dist	Fleet	Dist
R1 (25 c)	64	6372	53	6561	58	5732
C1 (25 c)	34	3167	31	3152	32	3014
R1 (50 c)	107	12036	92	12089	101	11307
C1 (50 c)	60	6712	53	7093	58	6682
R1 (100 c)	181	17907	150	17348	164	16680
C1 (100 c)	121	16011	108	16512	113	15206

Table 1: Results summary

sets of problems have been defined: C1, C2, R1, R2, RC1 and RC2. The customers are geographically uniformly distributed in the problems of type R, clustered in the problems of type C, and a mix of customers uniformly distributed and clustered is used in the problems of type RC. The problems of type 1 have narrow time windows (very few customers can coexist in the same vehicle's route) and the problems of type 2 have wide time windows. Finally, a constant service time is associated with each customer, which is equal to 10 in the problems of type R and RC, and to 90 in the problems of type C. We choose to use Solomon benchmarks, while following the modification proposed by [9] to make the problem dynamic. We have implemented three MAS with almost the same behavior, the only difference concerns the measure used by Vehicle agents to compute the insertion cost of a customer. For the first implemented MAS, it relies on the Solomon measure (noted Δ Distance), on the space-time model for the second (noted Δ Space-Time). We choose to run our experiments with the problems of class R and C, of type 1, which are the instances that are very constrained in time (narrow time windows).

Table 1 summarizes the results where we consider successively 25, 50 and 100 customers. The results show, with the two classes of problems, that the use of the space-time model mobilizes less vehicles than the spatial model, which in turn behaves better than the traditional measure, whatever the number of considered customers. These results validate the intuition of the models that consists of maximizing the future insertion possibilities for a *Vehicle* agent. Once this result validated, it is interesting to check the results with respect to the total distance traveled by all the vehicles. With respect to this criterion, the space model behaves better than the two others, while the behavior of the space-time model is less efficient, since it gives better results for the problems C1 with 25 customers and R1 with 100 customers, but is dominated by the traditional measure for the others. The fact remains that our results for both models provide better results than the traditional heuristic, provided the primary objective of the problem, which is to minimize the number of vehicles mobilized by the system.

7. CONCLUSION

In this paper, we have proposed two agent-oriented selforganization models for the dynamic VRPTW based on the agents' action zones. The action zones of the *Vehicle* agents reflect their coverage of the transportation network. We use the variation of these action zones as a new metric between *Vehicle* agent to reduce the myopic behavior of traditional metrics. By optimizing the coverage of the environment by the *Vehicle* agents, our model allows the MAS to self-adapt by exhibiting an equilibrated distribution of the vehicles, and to lessen this way the number of vehicles mobilized to serve the customers.

The models developed in this paper offer two solutions with different advantages, which allow a decider to choose the model to use following the operational configuration of the real problem faced. In the case where the transportation operator has a limited vehicles fleet, and where the mobilization of a new vehicle is costly, it is undeniable that the system should be grounded on the space-time model, which mobilizes less vehicles. In contrast, in certain real problems, the operator has a virtually unlimited fleet of vehicles, and the costs in term of traveled distance are more critical. Indeed, certains systems relie on a fleet of vehicles, which besides offer a traditional individual taxi service. In this kind of systems, it is more interesting to ground it system on the spatial model.

Our current work is oriented towards taking into account historic data of customers requests on the network nodes. We use these data as a weighting of the action zones of the *Vehicle* agents that concern the nodes frequently requested, and this to make them converge towards high density zones in the right time. Besides, the assessment the impact of breakdowns, noshows and other dynamic changes in the environment, on the solving process is also an ongoing research.

8. REFERENCES

- R. Bent and P. Hentenryck. A two-stage hybrid local search for the vehicle routing problem with time windows. *Transportation Science*, 38(4):515Ű530, 2004.
- [2] Z. J. Czech and P. Czarnas. A parallel simulated annealing for the vehicle routing problem with time windows. In *Proceedings of the 10th Euromicro* Workshop on Parallel, Distributed and Network-based Processing, pages 376–Ü383, Canary Islands (Spain), 2002.
- [3] G. Desaulniers, J. Desrosiers, M. Solomon, F. Soumis, and J.-F. Cordeau. The VRP with time windows. In D. Vigo and P. Toth, editors, *The Vehicle Routing Problem*, SIAM Monographs on Discrete Mathematics and Applications, pages 157–193. SIAM, 2002.

- [4] M. Diana. The importance of information flows temporal attributes for the efficient scheduling of dynamic demand responsive transport services. *Journal of advanced Transportation*, 40(1):23–46, 2006.
- [5] K. Fischer, J. Muller, M. Pischel, and D. Schier. A model for cooperative transportation scheduling. In V. R. Lesser and L. Gasser, editors, *Proceedings of the First International Conference on Multiagent Systems* (*ICMAS'95*), pages 109–116, Menlo park, CA (USA), 1995. AAAI Press / MIT Press.
- [6] L. Fu and S. Teply. On-line and off-line routing and scheduling of dial-a-ride paratransit vehicles. In *Computer-Aided Civil and Infrastructure Engineering*, volume 14, pages 309–319. Blackwell Publishers, Oxford (UK), 1999.
- [7] L. M. Gambardella, E. D. Taillard, and G. Agazzi. MACS-VRPTW: A multiple ant colony system for vehicle routing problems with time windows. In M. D. D. Corne and F. Glover, editors, *New Ideas in Optimization*, pages 63–76, McGraw-Hill (London), 1999.
- [8] M. Gendreau, F. Guertin, J.-Y. Potvin, and R. Séguin. Neighborhood search heuristics for a dynamic vehicle dispatching problem with pick-ups and deliveries. *Transportation Research Part C*, 14:157–174, 2006.
- [9] M. Gendreau, F. Guertin, J.-Y. Potvin, and E. D. Taillard. Parallel tabu search for real-time vehicle routing and dispatching. *Transportation Science*, 33(4):381–390, 1999.
- [10] B. Golden, S. Raghavan, and E. Wasil. The vehicle routing problem, latest advances and new challenges, volume 43 of Operations research/computer science interfaces. Springer Verlag, 2008.
- [11] J. Homberger and H. Gehring. Two-phase hybrid metaheuristic for the vehicle routing problem with time windows. *European Journal of Operational Research*, 162:220Ű238, 2005.
- [12] M. E. Horn. Fleet scheduling and dispatching for demand-responsive passenger services. *Transportation Research C*, 10(1):35–63, 2002.
- [13] H. Housroum, T. Hsu, R. Dupas, and G. Goncalves. A hybrid ga approach for solving the dynamic vehicle routing problem with time windows. In I. C. Society, editor, *Proceedings of the IEEE Conference on Information and Communication Technologies: from Theory to Applications*, pages 3347–3352, Damascus, Syria, 2006.
- [14] T. Ibaraki, S. Imahori, K. Nonobe, K. Sobue, T. Uno, and M. Yagiura. An iterated local search algorithm for the vehicle routing problem with convex time penalty functions. *Discrete Applied Mathematics*, 156(11):2050Ű2069, 2008.
- [15] T. Ibaraki, M. Kubo, T. Masuda, T. Uno, and M. Yagiura. Effective local search algorithms for the vehicle routing problem with general time window constraints. *Transportation Science*, 39(2):206Ű232, 2005.
- [16] M. Jepsen, B. Petersen, S. Spoorendonk, and D. Pisinger. Subset-row inequalities applied to the vehicle-routing problem with time windows. *Operations Research*, 56(2):497–511, 2008.
- [17] R. Kohout and K. Erol. In-Time agent-based vehicle

routing with a stochastic improvement heuristic. In Proceedings of the sixteenth national conference on Artificial intelligence and the eleventh Innovative applications of artificial intelligence (AAAI'99/IAAI'99), pages 864–869, Menlo Park, CA (USA), 1999. AAAI Press.

- [18] A. Larsen. The Dynamic Vehicle Routing Problem. PhD thesis, University of Denmark, 2000.
- [19] A. Lim and X. Zhang. A two-stage heuristic with ejection pools and generalized ejection chains for the vehicle routing problem with time windows. *INFORMS Journal on Computing*, 19(3):443Ű57, 2007.
- [20] D. Mester and O. Bräysy. Active guided evolution strategies for large scale vehicle routing problems with time windows. *Computers & Operations Research*, 32(6):1593Ű1614, 2005.
- [21] Y. Nagata, O. Bräysy, and W. Dullaert. A penalty-based edge assembly memetic algorithm for the vehicle routing problem with time windows. *Computers & Operations Research*, xx(x), July 2009.
- [22] D. Pisinger and S. Ropke. A general heuristic for vehicle routing problems. *Computers & Operations Research*, 34(8):2403Ű2435, 2007.
- [23] R. G. Smith. The contract net protocol: High-level communication and control in a distributed problem solver. *IEEE Trans. on Comp.*, C-29(12):1104–1113, December 1980.
- [24] M. Solomon. Algorithms for the vehicle routing and scheduling with time window constraints. Operations Research, 15:254–265, 1987.
- [25] K. P. Sycara. Multiagent Systems. AI Magazine, 19(2):79–92, 1998.
- [26] S. R. Thangiah, O. Shmygelska, and W. Mennell. An agent architecture for vehicle routing problems. In *Proceedings of the 2001 ACM symposium on Applied computing (SAC '01)*, pages 517–521, New York, NY (USA), 2001. ACM Press.
- [27] M. Wooldridge and N. R. Jennings. Intelligent agents: Theory and practice. *Knowledge Engineering Review*, 10(2):115–152, 1995.
- [28] M. Zargayouna. Une représentation spatio-temporelle de l'environnement pour le transport à la demande. In Atelier: Représentation et raisonnement sur le temps et l'espace, Plate-forme AFIA 2005, Nice (France), 2005. in french.
- [29] M. Zargayouna. Modèle et langage de coordination pour les systèmes multi-agents ouverts. Application au problème du transport à la demande. Phd Thesis, University of Paris-Dauphine, Paris (France), 2007. In french.
- [30] K. Q. Zhu and K.-L. Ong. A reactive method for real time dynamic vehicle routing problem. In 12th IEEE International Conference on Tools with Artificial Intelligence (ICTAI'00), pages 176–179, Vancouver (Canada), 2000. IEEE Computer Society.