Time constrained VRP: an agent environment-perception model

Mahdi Zargayouna[1]

Abstract. In this paper, we present a multiagent model in which agents have a perception upon their shared environment, a measure is associated to the agents' perception field. We apply the model on the Vehicle Routing Problem with Time Windows (VRPTW). The overall process adopts the general schema of parallel insertion methods and it uses the contracting of perception's field of the vehicle agents as a new distance between them. This new measure expresses the feasibility universe of the vehicles and is used as a criterion of choice between candidates vehicles for the insertion of a customer in their plan. Our approach provides a new method to tackle the Time constrained VRP in which the solving process is focused on the future and constitutes an alternative for handling the dynamic version of the problem.

1 Introduction

Vehicle routing problems (VRP) have been an intensive research area in the last decades because of their large applicability in real life problems. Several constrained variants were proposed in order to meet specific operational applications, they concern time restrictions, requests configuration etc. One of the most widely studied problem is the time (and capacity) constrained version: the Vehicle Routing Problems with Time Windows (VRPTW henceforth). VRPTW and their variants (PDPTW, DARPTW etc.) are hard combinatorial optimization problems. Exact approaches for the static VRPTW are only of theoretical interest and artificial intelligence heuristics succeeded in finding good solutions, within reasonable computational times. In the dynamic problem, the whole customers set is not available before the start of execution.

In this paper, in order to tackle the dynamic VRPTW, we consider that zero demands are known *a priori*. To this purpose, we propose to model a multiagent system (MAS henceforth) composed of *vehicle* agents, a queue of *customer* agents and events representing customers' requests occurring *ad hoc*. They evolve in the same environment in which they are described by their observable descriptors. *Vehicle* agents' perception field is modeled as a subpart of the environment observation domain and is quantified. *Customer* agents select the vehicle into which they want to belong following a criterion: the minimal decrease of the *vehicle* agent's perception field quantification. This criterion helps us in dealing with uncertainty concerning future (unknown) customers' demands. The remainder of the paper is then organized as follows. In the next section, we first present a generic model of the environment and of the agents' perception, then its application to the VRPTW problem. In section 3, we conclude and give some perspectives to our work.

[1] Inrets institute and Paris-Dauphine University, France, email: zargayou@inrets.fr

2 Our proposal

2.1 Multi-Agent environment and Agents' perception

Our environment model could be seen as an extension of [1, 6]. Our definition is based on the principle of observability i.e. the entities' external description. The formulation is inspired from the Symbolic Data Analysis paradigm [2].

Definition 1 (Environment) $ENV = \langle A, E, Y, M\rangle$ *with:*
• $A = \{a_1, ..., a_m\}$ *a set of agents,*
• $E = \{e_1, ..., e_n\}$ *a set of events,*
• $Y = \{y_1, ..., y_p\}$ *a set of variables (functions)*
$Y : A \cup E \to \Omega$
$\Omega = \prod_{i=1}^{p} \Omega_i$, *with* Ω_i *the description domain of the variable* y_i,
• $M : \prod_{i \in I} \Omega_i \to \mathcal{P}(A), I \subseteq \{1..p\}$

In addition, to every agent a_k, we associate:
$Restr_k : \prod_{i \in I_k} \Omega_i \to \{true, false\}, I_k \subseteq \{1..p\}$
A quantification: $\| a_k \| \in \mathbb{R}^+$
Every agent and every event are accessible via their observable descriptions (set of variables). To every agent a_k, we associate a conjunction of perception restrictions (assertions, we note $Restr_k$) on the values of the variables it wants to perceive (I_k is defined by a_k). If $Restr_k$ is empty then a_k can perceive everything. To every $Restr_k$ of an agent a_k, we associate a quantity in $\mathbb{R}^+$ ($\| - \|$) which reflects the capacity of perception of agent a_k, based on its restrictions $Restr_k$. For instance, if $Y = \langle age, sex\rangle$, $\Omega = [0, 100] \times \{\text{“}male\text{”}, \text{“}female\text{”}\}$, and $Restr_1 = \langle sex = \text{“}male\text{”} \wedge age \geq 50\rangle \Rightarrow \| a_1 \| = 1 \times 50 = 50$.
The environment is responsible of the aggregation of the different $Restr$ of the agents -via the function M- in order to know, when an agent or an event reveals to the system (partially defined by $\bigcup_{i \in I} y_i$ with $I \subseteq \{1..p\}$), which agent actually perceives it.
Analogically to the Symbolic Data Analysis paradigm, every function $Restr_k$ is a symbolic object which extension is composed of $Ext_k = \{\omega / Restr_k(\omega) = true\}$.
Such an abstraction of the environment can model any MAS where the environment is a first-class abstraction [5] i.e. the environment is an explicitely designed entity. Note that to our knowledge, in the domain of the modeling of environment for multiagent systems, there is no propositions in the literature that quantify the agents' perception.

2.2 Application: the VRPTW problem

The VRPTW problem is a multi-vehicle Traveling Salesman Problem with limited capacity and with time intervals associated to the nodes to be visited. We consider an Euclidean VRPTW for presentation clarity (distances and time-travel computed following the Euclidean metric). In our system, we have two types of agents: *customer* agents and *vehicle* agents. *customer* agents are in a queue, they sequentially reveal to the system and each one is considered independently from its successors. Every *customer* agent is described by (x, y, e, l, s, q), with (x, y) its cartesian coordinates, $[e, l]$ its time window, s its service time, and q its requested quantity. Each *vehicle* agent is described by *cap* its capacity and is initially located at a depot. The overall process is greedy-like and is based on a CNP (*Contract Net Protocol* [3]), where every *vehicle* agent that is able to visit the considered customer (w.r.t the customers already inserted in its plan) proposes an offer, and the best offer (following a criterion that we defined, see below) is retained by the *customer* agent. In order to be perceived by the *vehicle* agents, a *customer* agent, when it is its turn to reveal to the system, creates events representing it by discretizing its time window $[e, l]$ and puts them in the environment, every event is then described by (x, y, s, t, q). The offer computed by every *vehicle* agent is equal to its contracting of perception i.e. the decrease of its perception quantification as presented in the model. The initial restrictions, say $Restr_0$ of a *vehicle* agent, say v_0, following the Euclidean metric and the capacity constraints, are equal to:

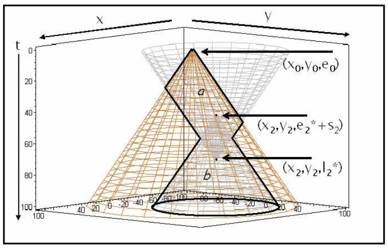

Figure 1. Space-time perception

$$Restr_0 = ([(x - x_0)^2 + (y - y_0)^2]^{1/2} \leq (t - t_0)) \wedge (q \leq cap_0)$$

(x_0, y_0, t_0) are the cartesian coordinates of the depot and the scheduling starting time (constants) and cap_0 the initial capacity of the vehicle v_0. From the point of view of an agent, following this inequality, the environment is a hypercube of four dimensions (two for the cartesian coordinates x, y, one for the time t and one for the capacity q). Initially, $\| v_0 \|$ is equal to the volume of the cone of vertex (x_0, y_0, t_0) (cf. Figure 1, the big cone) multiplied by cap_0. Now, let us consider a *customer* agent c_2 described by $(x_2, y_2, e_2, l_2, s_2, q_2)$. Suppose that v_0 perceived a subset of the events describing it. v_0 computes the new time-window values e_2^*, l_2^* [2], and computes its new $Restr_0$ and $\| v_0 \|$. The new $Restr_0$ is equal to $[a] \vee [b]$ with:

$$[(x - x_2)^2 + (y - y_2)^2]^{1/2} \leq (l_2^* - (t + s)) \qquad [a]$$
$$[(x - x_2)^2 + (y - y_2)^2]^{1/2} \leq (t - (e_2^* + s_2)) \qquad [b]$$

$[a]$ is the condition to be satisfied by any customer if it had to be inserted before c_2 and $[b]$ is the condition it has to satisfy if it had to be inserted after c_2. The new quantification $\| v_0 \|$ is equal to the volume of the intersection of the old cone with the union of the two new cones described by $[a]$ and $[b]$ (cf. Figure 1), multiplied by the new cap_0 $(= cap_0 - q_2)$. v_0 is a candidate for the insertion of c_2, the offer it will propose is $\Delta_{\|-\|}$, the difference between its old and it new perception quantification, which is equal to $\| v_0 \|_{new} - \| v_0 \|_{old}$. c_2 selects the vehicle with the minimum loss of perception $\min_{\Delta_{\|-\|}}$. This criterion expresses the decrease of the probability for a vehicle to be a candidate for future customers' demands.

We ran our system on the Solomon's benchmark [4]. Although our system could not actually be compared to any state-of-the-art works, because our proposal is the only one that could work with zero known demands, we compared it with the best known static systems focusing on the verification of two results: the computational times' variation and the explosion of the number of vehicles used. The results showed that the computational times increase slowly with respect to the number of considered customers, which makes our proposal a good candidate to operate in a dynamic configuration. The gap in the number of vehicles used by our system w.r.t those used by the best algorithms is of 50% when considering 100 customers and 16% when considering 200 customers, thus the fleet of vehicles remains stable even assuming this handicaping scenario.

[2] how to recompute e_2^* and l_2^* is out of the scope of this paper

3 Conclusion and perspectives

In the state-of-the-art approaches, all the works try to handle the dynamic requests in the VRPTW by, firstly, considering a subpart of requests known in advance. Secondly, some of them try to reconsider previous requests assignment in order to increase the quality of the solution, which is time consuming. We try to follow neither the first nor the second approach: no customers are known in advance (the newly incoming ones simply enqueue themselves), and every assignment is definitive. We present a generic multi-agent model based on the observability principle, we quantify agents'perception and we use the loss of perception as a new distance between partial *vehicle* agents' plans in order to lessen the myopic behavior of the traditional metrics. This model provides a new method to tackle the dynamic VRPTW in which the solving process is focused on the future. Future works will consider variants of the VRPTW such that the Pickup and Delivery Problem with Time Windows and the Dial-A-Ride problem, the latter problem fits very well with the multiagent paradigm since customers also try to maximize their own utility.

REFERENCES

[1] Balbo, F., Pinson, S.: "Toward a Multi-Agent Modelling Approach for Urban Public Transportation Systems", in Omicini A., Petta P. et Tolksdorf R. (eds), Engineering Societies in the Agent World II, LNAI 2203, Springer Verlag (2001) pp 160–174.

[2] Bock, H.H., Diday, E. (eds.): "Analysis of Symbolic Data. Exploratory Methods for Extracting Statistical Information from Complex Data", Series: Studies in Classification, Data Analysis, and Knowledge Organisation, Vol. 15, Springer-Verlag, Berlin, Germany (2000), 425 p.

[3] Davis, R., and Smith, R.G. : "Negociations as a metaphor for distributed problem solving. Artificial Intelligence 20:63-109, 1983.

[4] Solomon M. : "Algorithms for the vehicle routing and scheduling with time window constraints", in Operations Research 15, (1987), pp 254-265.

[5] Weyns, D., Parunak, H.V.D., Michel, F., Holvoet, T. Ferber, J.: "Environments for Multiagent Systems, State-of-the-art and Research Challenges", in Proceedings of Workshop on Environments for Multi-Agent Systems (E4MAS) LNAI 3374 Springer Verlag (2004) pp 1-47.

[6] Zargayouna, M., Balbo, F. and Saunier, J.: "Agent Information Server: a middleware for traveler information", In Lecture Notes of Artificial Intelligence, Vol.3963, 2006.