13th IFAC Symposium on Control in Transportation Systems
The International Federation of Automatic Control
September 12-14, 2012. Sofia, Bulgaria

Distributed approach for vehicle routing problem in disaster case

F. Mguis*, K. Zidi, K. Ghedira*** and P. Borne******

**Higher Institute of Management of Tunis
Tunisia (Tel: 00216 22 650 375; e-mail: fethi.mguis@fsg.rnu.tn).
**Faculty of science of Gafsa
Tunisia (e-mail:k.zidi@yahoo.fr
*** Higher Institute of Management of Tunis
Tunisia, (e-mail: khaled.ghedira@isg.rnu.tn)
**** Ecole Centrale de Lille
France, (e-mail: pierre.borne@ec-lille.fr)*

Abstract: The present study aims to solve the vehicle routing problem in disaster case. We have decomposed such problem into two parts; the first one concerns the vehicle routing planning to serve several requests, while, the second one concerns the treatment of an eventual event including the arrival of a new demand and the appearance of a disturbance. Besides, we proposed a multi-agents approach using a genetic algorithm for scheduling vehicle routing and local search for the management of an eventual event. The proposed approach was tested with the modified Solomon benchmarks and gave good results.

Keywords: Vehicle Routing Problem, emergency, multi-agent system, genetic algorithm, local search.

1. INTRODUCTION

In the case of a disaster, the logistics department occupies a prominent place. Indeed, the intervention must be quick and well organized. In addition, each decision must take into account all parameters. These parameters, in case of disaster, are very dynamic. Among the most important tasks of the logistics services is to organize the vehicles tours and later to serve all customer's requests. The offered services were divided to different types: passenger transport civilians, troops transport, freight, distribution of food, distribution of fuel, distribution of drug, etc. To accomplish such services a heterogeneous fleet of vehicles was used. Generally, in disaster case, customers must be served in well-defined time windows. In addition to all the time, you can have new demands or new constraints. So the problem described here can be considered as a dynamic vehicle routing problem with time windows (DVRPTW).

In this paper we used a multi-agent approach to solve a dynamic vehicle routing problem with time window.

2. VEHICLE ROUTING PROBLEM

The vehicle routing problem VRP, as it was defined by [Dantzig and al 1959], was the optimization of one or more criteria to construct a set of tours, for a limited number of vehicles, starting and ending at a depot. In these tours, each customer must be served only once and by one vehicle. Furthermore, the transport ability of the vehicle for one tour must not be surpassed.

The vehicle routing problems play an important role in the planning and management of retail chains. Many researchers were committed to invest in this area of research and this especially during the last five decades. Most of these works concerned the static VRP. But in real life, some parameters are dynamic, requiring a readjustment of tours already planned. With new communication technologies that enable access to real-time data, dynamic VRP become increasingly studied. Generally, the DVRP was decomposed into a set of static problems. Then the resolution algorithm was applied to each static problem. But it remains to determine which algorithm can provide workable solutions, good quality, and a reasonable time for each static problem. Meta-heuristics have shown great performance in solving such problems. Among the most meta-heuristics used for solving the VRP and its variants we found the genetic algorithm which generates a population of solutions. On the other hand the multi-agent systems provide good supervision system, an exchange of information more efficient and a faster response time. The DVRPTW could be modeled using a multi-agent for the following reasons. First, it is a difficult problem for which the exact methods only deal with smaller versions which in turn cannot represent a real-world applications. The choice of a model for the treatment distribution may be a solution to provide fast response according to the customer demands. Then there is a problem that requires active management of data. By definition, all data are not available before the start of the implementation and further, the system must adapt to the reality of the transmission system disturbance, failure, etc. Furthermore, with technological development, it is reasonable to consider vehicles with embedded computational capabilities. In this context, the problem is, in fact, distributed and requires a suitable model to take advantage of embedded capabilities of the vehicles. Finally, consideration of a multi-viewpoint agent can imagine

978-3-902823-13-7/12/$20.00 © 2012 IFAC

10.3182/20120912-3-BG-2031.00073

new measures, new heuristics, not envisaged by centralized approaches.

A solution to this problem is to make all trips to ensure the visit all customers. The proposed routes must comply with various constraints is the ability of vehicles and customers temporarily. The test most used in this kind of problem is to minimize the total distance traveled with a minimum number of vehicles. In addition, we must respond to requests that arrive during the execution and must be taken into account the new constraints that may occur.

2.1 Vehicle routing problem with time windows

Defining the problem

The vehicle routing problem with time windows VRPTW is an extension of vehicle routing problem described above. In VRPTW, new time constraints are added: each customer must be served for a time interval during which it can be visited [Cordeau and al 2000b]. In fact the vehicle that will serve the customer *i* must get there before the end of its time window. If the vehicle arrives at the customer before the start of the time window must wait until the beginning of the time window. In addition, each customer has a service life well determined. So solving this problem is to find the best planning tours of the vehicles with minimum total distance traveled, the total minimum time and minimum waiting time for vehicles to customers using the minimum number of vehicles.

Mathematical formulation of the problem

In this section, we present a mathematical formulation for the vehicle routing problem with time windows proposed by [Zeddini et al 2009].

An instance $I = (G, D, T, S, F, R, \kappa)$ of the problem VRPTW is defined as follows. Let $G = (V, E)$ be a graph with a set of nodes $V = \{(v_i)\}, i = \{0, \dots, N\}$ (v_0 node is the depot) and a set of edges $E = \{(v_i, v_j) | v_i \in V, v_j \in V, v_i \neq v_j\}$. Given two matrices $D = \{(d_{ij})\}$and $T = \{(t_{ij})\}$of cost, size N * N (arc (v_i, v_j) has a cost-distance d_{ij} and cost time t_{ij}), a M Table F-vehicles, and an N-tuples of tables R $(q_i, s_i, [e_i, l_i])$ (v_i node has a demand q_i, a service time s_i, and a time window $[e_i, l_i]$). A vehicle must be level before i l_i but it can be at before i e_i and in which case it must wait until the service begins. Each customer request is assumed to be less than κ. Two decision variables are defined: $X = (x_{ij}^k)$ of dimension N * N * M and $B = (b_i)$ of dimension N having the following meaning:

$$x_{ij}^k = \begin{cases} 1 \text{ if vehicle k travel between clients i and j} \\ 0 \text{ otherwise} \end{cases}$$

$b_i = t \Leftrightarrow v_i$ is served at *t*

The function to be optimized is:

$$min \sum_{i,j=0}^{N} c_{ij} \sum_{k \in F} x_{ij}^v \ (1)$$

Under the constraints:

$$\sum_{k \in V} \sum_{j=1}^{N} x_{ij}^k = 1 \ \forall \ v_i \in V - \{v_0\} (2)$$

$$\sum_{j=1}^{N} x_{0j}^k = 1 \ \forall \ k \in F (3)$$

$$\sum_{i=0}^{N} x_{ij}^k - \sum_{j=0}^{N} x_{ji}^k = 0 \ \forall k \in F \ et \ \forall \ v_j \in V - \{v_0\} (4)$$

$$\sum_{j=1}^{N} x_{j0}^k = 1 \ \forall \ k \in F (5)$$

$$\sum_{i=0}^{N} q_i \sum_{j=0}^{N} x_{ij}^k \leq \kappa \ \ \forall \ k \in F (6)$$

$$x_{ij}^k (b_i + s_i + t_{ij} - b_j) \leq 0 \ \forall \ k \in F \ et \ \forall (v_i, v_j) \in E (7)$$

$$e_i \leq b_i \leq l_i \ \forall \ k \in F \ et \ \forall \ v_i \in V (8)$$

$$x_{ij}^k \in \{0,1\}, \forall (v_i, v_j) \in E \ et \ \forall k \in F (9)$$

- The objective function (1) expresses the total cost.
- Constraints (2) ensure that every customer is served once per one and only one vehicle.
- Constraints (3) to (5) characterize the path to be followed by a vehicle k: K to leave the deposit once (3), if another vehicle serves, he should leave (4) and finally return to deposit only once (5).
- Constraints (6) ensure no violation of the capacity limits for all vehicles.
- Constraints (7) and (8) to ensure no violation of temporarily.

2.2 The dynamic vehicle routing problem

This problem can be defined as a static VRP problem but with the following differences [Larsen, 2000]:

1. The Information about planning tours is not fully known by the planner when the planning process begins. In other words, some of the problem depends explicitly on time (i.e. appearance of a new client).
2. The information may change after the initial rounds were built.

In our case the changes that can occur are:

- The appearance of a new request.
- The cancellation of a request.
- Changing the settings of one request (time window, service time, number called, etc.).
- The unavailability of a road.
- A vehicle that fails.

3. THE MULTI-AGENTS SYSTEM

3.1. Theoretical concepts

The field of Multi-Agents system appeared in the 80's with different nomenclatures: Distributed Artificial Intelligence, Artificial Intelligence and Decentralized Multi-Agents System DMA. The design of the MAS is applied in several scientific fields such as physics, biology, etc. in the literature, there are several definitions for the agent paradigm and the MAS, among which include those of Ferber [Ferber, 1995] defines an agent as a physical or virtual,

- Which is capable of acting in an environment,
- That can communicate directly with other agents,
- Which is driven by a set of tendencies (in the form of individual objectives or function of satisfaction, even survival, it seeks to maximize),
- Which has its own resources,
- Who is able to perceive (but limited) environment,
- Which has only a partial representation of this environment (and possibly none),
- With expertise and provides services,
- Who can possibly recur,
- Whose behavior tends to meet its objectives taking into account the resources and expertise available to it, and according to its perception, its representations and communications it receives.

Similarly, according to Ferber [Ferber, 1995], MAS is a system composed of the following:

- An environment E that is to say an area generally has a metric.
- A set of objects O. These objects are located, i.e. for each object, at some point, to associate a position in E. These objects are passive; that is to say, they can be perceived, created, destroyed and modified by the agents.
- A set A of agents, which are particular objects, which represent the active entities of the system s.
- A set of relations that unite R objects (and agents) between them.
- A set of operations Op enabling agents of A to perceive, produce, consume, transform and manipulate objects from O.
- Operators to represent the application of these operations and the world's reaction to this attempt to change.

4. THE LITERATURE REVIEW

Much work has been developed to solve different variants of the VRP based on multi-agent systems. In [Elfazziki and al, 2005], there was proposed a Multi-Agents modelling and optimization of management systems shipping VTS. This approach is to decompose the system into three subsystems. A sub-system planning is responsible for planning and management of freight and loading/unloading of goods. Ergonomic a subsystem is responsible for the management of ship captain. And a subsystem is responsible for overseeing the management of the fleet of ships. According to this decomposition, the authors used a Multi-Agents System consists of three types of agents: Supervisor Agent, Planner agent and Ergonomic agent. Companies are regarded as Supervisors agents, ships with their commanders, are considered Planner Agents, the tasks pertaining to the management of ships and commanders as Ergonomic agents. The Planner agent's role is the development of local plans, order delivery and negotiation with other staff planners. The Ergonomic agent's role the implementation of knowledge on a ship and routes necessary infrastructure management hardware and software, checking the proper maintenance of the ship, checking the presence of all the accessories, control Automatic ship and using the command. The supervisor agent’s role is cooperation with other supervisor’s agents, the issue of a tender, the collection of answers, sort of responses received, the contracting officer’s winners and waiting the results. Communication is carried out according to Contract-Net-Protocol which has three main stages: the tender, submission of proposals and awarding contracts.

In [Zhenggang and al, 2009], there was proposed a multi-agents enhanced to solve a vehicle routing problem with time windows VRPTW. This approach uses five types of agents. The first agent is the agent that receives the average adjuster demands of customers and delivers to the scheduler. The request contains a customer location, the time window and type of product. The second agent is the scheduler agent that manages the SMA and is primarily responsible for planning, management, coordination and control of other agents. The third agent is the vehicle agent, its role is that tracking capabilities of the vehicles, and time services, collection of applications, application processing, generation of offer and acceptance or rejection of applications. The last two agents are the GIS agent and the Interface agent that can receive and display information (position of a vehicle, location of a client, etc.). In real time, the improvement provided by this approach is at the negotiation protocol. Indeed the authors proposed an improved NOC. The improvement in response time by the fact that instead of sending an invitation to tender to all staff vehicles, the agent scheduler only interviews vehicles able to add the new request

In [Nabaa and al, 2007], there was proposed a decentralized approach to solve the problem of demand transport. The proposed MAS employ three types of agents: vehicle, Interface and Customer. Indeed, the arrival of a new customer, it sends a request containing an identifier, and source and destination to the interface agent; it broadcasts the request of the customer Vehicle agents that will calculate and negotiate the cost added new customer of them. Finally, the agent sends winning vehicle to the customer source and destination dates. The difference in this model compared to existing dynamic systems TAD is that applications are not batched but in real time. This model is based on two simultaneous phases, one phase to tender and a choice phase. The aim is to establish an agreement between the proposed transport and the customer's interests. A key element of the system is the matching between carrier and customer. What is the best carrier for a given application? Who determines and how? How the carrier knows that he was chosen? These issues are also not independent: for example if the carrier was able to determine himself that he was the best, the question to them about does not even arise. The carrier will match the user will be chosen by trying to minimize the extra mile for the carrier. For this extra effort, it suffices to calculate the length (in time) of the current route (cost) on the one hand, that the route to unload passengers over current setting and service to the user who applied on the other hand, and subtract the first to the second. This difference is the extra effort or extra cost. Determine the carrier is selected then select the one of least overhead among those to support the new applicant would not require flouting the deadline for service of at least one user already shipped. The request is broadcast to all carriers. They then calculate all their costs they spread to all. They order the responses received and then spread the top. The winner is determined by each carrier who has been most frequently ranked first in the responses received. The winner gets the new user.

In [Boudali and al, 2005], there was proposed an interactive distributed approach to the resolution of a VRPTW. The proposed approach uses two types of agents: Interface and Customer. The Interface agent's role is to initialize the resolution process, coordination between its various components and detecting the end. Customer agent will coordinate with other customer's agents to be served with minimum cost. Each Customer agent is characterized by a static body of knowledge (ID, address, time window, length of service, amount requested, vehicle capacity, list of his children, his parents' list, list of ancestors, list of his descendants, and its distance from other customers) and a dynamic body of knowledge (individual solution, the steady state solution in his individual statements of customers in touch with him ...). The resolution process is contained two steps. The first step is the generation of the graph of relationship. During this phase, each Customer agent i sends messages to customer agents j likely to be parents of i. j is the parent of i if and only if $x_j-\alpha \le x_i \le x_j+\alpha$; $y_j-\alpha \le y_i \le y_j+\alpha$ et $s_j+t_{ji} \le l_i-e_j$. The second phase is to determine the best coalition for each client. Coalitions are generated dynamically.

In [Zeddini and Zargayouna, 2009], there was proposed a model of self-organization to solve a dynamic VRPTW. The proposed model uses three types of agents: Interface, Vehicle and Customer and is intended to allow agents to cover an area of vehicle space-time maximum of the transmission network. This model is based on measuring the zones of action of vehicle as the cost of insertion. The action area of a vehicle is defined as the number of clients can be served by the vehicle. If a vehicle is located at the depot (x_0, y_0) at time t_0, customers (x, y) are available for this vehicle described by the following inequality:

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

The cost of inserting a customer in the tour of a vehicle shall be the measure associated with the former zone of action of the vehicle unless the extent of the new area of action, after the insertion of the customer. The amount represents the positions and measured space-time that the vehicle can no longer be, if he had to put that customer in its plan. The vehicle chosen to service a customer is which the insertion of the customer unless it reduces its area of space-time action. This corresponds to choose the vehicle that loses the least opportunity to be a candidate for future customers.

5. PROPOSED APPROACH

Our approach consists to decompose the problem into a set of sub-problems (Fig. 1). Each sub problem is to use a set of customers with a single vehicle (traveling salesman problem TSP). So the sum of the quantities requested by customers of the same group must not exceed the capacity of the vehicle. For the decomposition of the problem, we used a distributed version of the genetic algorithm. For solving the TSP, we developed a heuristic for determining the shortest path.

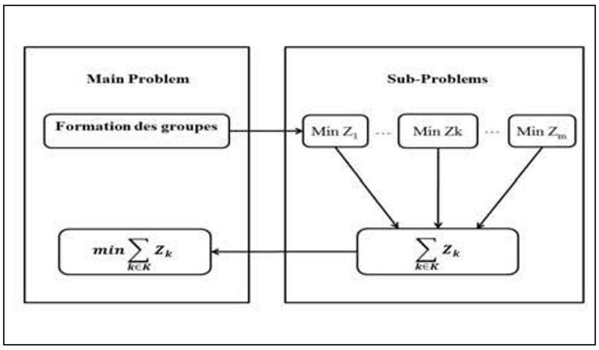

Fig. 1. Decomposition of the problem

5.1. Genetic algorithm

The basic principles of these algorithms were given by [Holland, 1975]. These algorithms are based on the operation of the natural evolution of species, including the selection of Darwin and Mendel procreation. They have been effectively used to solve several multi-criteria optimization problems [Coello, 2001].

In genetic algorithms, we simulate the process of evolution of a population. We start with an initial population composed of N solutions (individuals) of the problem. The degree of adaptation from one individual to the environment is expressed by the value of the cost function f (x) where x is the solution that the individual represents. It is said that an individual is even better adapted to its environment, the cost of the solution is lower or larger depending on selected criteria optimization. Within this population, occurs when the random selection of one or two parents, producing a new solution, through genetic operators such as crossover and mutation. The new population, obtained by choosing N individuals among populations (parents and children), is called next generation. By iterating the process, we produce a population richer in individuals best suited. The process of genetic algorithm is presented in Fig. 2.

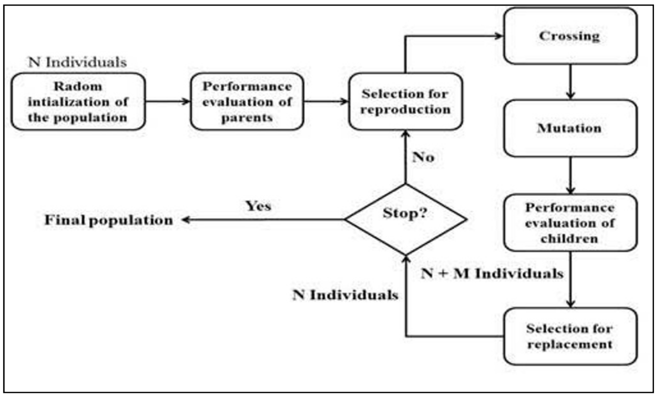

Fig. 2. Principle of genetic algorithm

For the success and the convergence of the genetic algorithm, you must:

- Make a good representation (coding) of a solution (chromosome),
- choose the manufacturer of the initial solution,
- clearly identify the evaluation function to determine the fitness of each individual,
- choose the methods of selection, crossover and mutation are best suited to the problem and,
- carefully choose the parameter values: population size, probabilities, etc.

The Coding

Since the binary chromosomes are not adopted for problems of sequencing, we have adopted a real encoding where the chromosome is a sequence of nodes (excluding the deposit) without parameters delimiters. We mention the different characteristics (number of tours, number of customers in each tour and the overall cost of the solution) of rounds in a table accompanying the chromosome. Fig. 3 shows a chromosome consists of three tours and its characteristics.

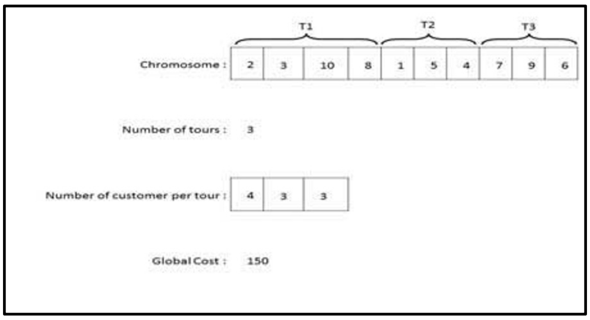

Fig. 3. Example of a chromosome

Creating the initial population

To build the initial population, it has developed a heuristic that builds the chromosomes randomly.

The Selection

To select the chromosomes (solutions) that will be able to contribute to the creation of the new population, we adopted the method of selection of Wheel [Holland 1975] [Goldberg 1989], which is to give each individual a probability of selection proportional to its evaluation (fitness) and the sum of the individual assessments. The process of selection is presented by the following algorithm:

Algorithm selection:

1. Calculating the fitness f_i for each individual of the population
2. Calculating the probability Pi of selection of each individual $P_i = f_i / \sum_{i=1}^{i=n} f_i$
3. Calculation of cumulative probability qi of each individual $q_i = \sum_{j=1}^{i} p_j$
4. Generate a random value $r \in [0,1]$
5. If $r < q_1$ then select the first individual else choose individual i as: $q_{i-1} < r \leq q_i$
6. Repeat steps 4 and 5 to create the desired number of individual

The crossover operator

From both parents (solutions), we try to generate a son (a solution) that is achievable. There are several breeding techniques. For each type of problem, there are a set of crossing methods which are more suitable. For the vehicle routing problem, according to the literature, the most common methods are: the point crossover, tow point crossover and uniform crossover. In our case we used the latter type of crossing. The uniform crossover is to calculate the cost of each tour for both parents. Then turned on each parent is sorted in ascending order by the quotient Cost of tour / Customer number of tour. The construction of the individual son is as follows: we start by adding the first tour of the first parent and removing all tours of the second parent that conflict with the tour added. Then we did the same with the first tour available of the second parent. After we return to the first parent and so on until there are more tours to be added. Customers were not included will be added to the end of chromosome son. Fig. 4 shows an example of uniform crossover.

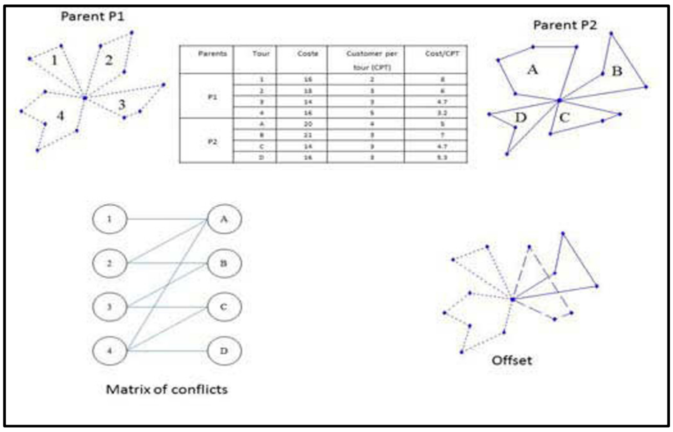

Fig. 4. Example of a uniform crossover operation

The mutation

During the process of evolution, the mutation makes a broad exploration of the research space, to avoid premature convergence or loss of diversity by bringing innovation in the population. In our approach we have adopted the method of simple random mutation. The principle of this method is to choose randomly, a tour and a node of this tour. After, a random value between 0 and 1 is chosen. If this value is less than the mutation probability, the node will be inserted at the best location in the same tour, otherwise another tour will be randomly chosen and the customer will be inserted in the best location in this tour. Fig. 5 shows an example of a mutation operation.

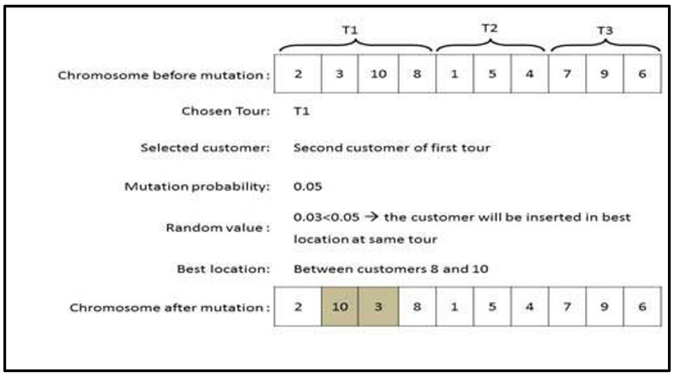

Fig. 5. Example of mutation operation

The replacement

After each iteration, individuals created (children) will be added to the population. To keep the same population size, we proceed to an elitist replacement operation is to sort the individuals according to their overall costs and we only keep the first N individuals to form the next generation.

5.2 Heuristic for solving the TSP

We developed a heuristic for solving a TSP within the constraints of temporary clients. Our heuristic is to sort nodes in ascending order according to their end dates of service. If two nodes have same end dates of service, the nearest will be served first.

5.3 Multi-Agent model

In this section we present the architecture of our SMA. This allows for vehicle routing plan to serve a set of applications in an emergency. The proposed approach can also manage the unforeseen events that can occur as the arrival of a new request or the appearance of a perturbation. The SMA defined (Fig. 7) provides for the use of three agents: Supervisor Agent, Vehicle Agent and Interface Agent.

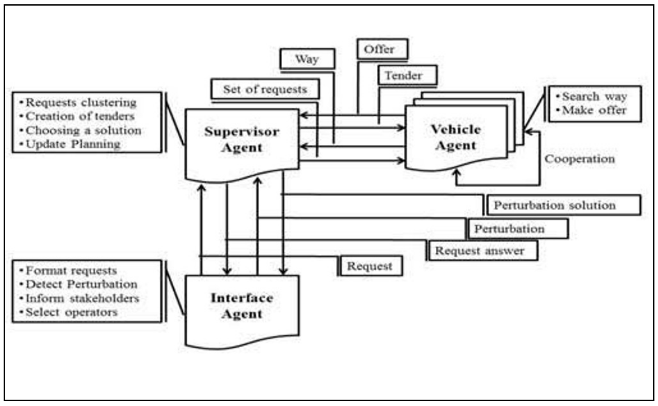

Fig. 6. Architecture of Multi-Agent System

Supervisor Agent

The supervisor agent is both responsible for the supervision of the entire system. On the other hand, it performs the following tasks: management of tenders, selection of the best solution, the consolidation of applications and updates to the schedule.

Interface Agent

The Interface Agent is mainly concerned with all aspects of communication system with the external environment, namely service providers and requesters of services. Indeed Agent Interface is responsible for receiving applications, the selection of operators, data extraction, information from stakeholders and the detection of disturbances.

Vehicle Agent

The main task of an agent vehicle is the development of his way. He must be able to make deliveries sound control in different areas, generating local plans and negotiate with other vehicle's agent to minimize the overall cost.

5.4 Resolution of the dynamic part of the problem

Most conventional approaches proposed to solve these problems are to consider dynamic that every change creates a new optimization problem to be solved again from scratch. However, although the idea is simple, it is often inapplicable in a context in tight time constraints as in the case of a disaster. Indeed, the problem solving NP-hard type usually takes too long to find solutions of good quality. Often, the solution of the new problem does not differ too much from the previous solution of the problem when the environment is weakly perturbed, which is generally the case in our case. So why not reuse the old solutions to provide new solutions that address the disruption? It is this possibility that we operate within the framework of our approach. For this, we implemented a local search heuristic to provide a workable solution.

6. COMPARISON OF EXPERIMENTAL RESULTS

In this section we compare the results obtained with our approach described above with the results of Ant Colony Optimization algorithm by [Gambardella and al., 1999] and Tabu Search algorithm by [Cordeau and al., 2000a]. For comparison purposes we used the most well-known 100-customer benchmark problem set by [Solomon, 1987]. In these problems, the travel times are equal to the corresponding Euclidean distances. The geographical data were either randomly generated using a uniform distribution (problem sets R1 and R2), clustered (problem sets C1 and C2) or mixed with both randomly distributed and clustered customers (problem sets RC1 and RC2). Problem sets R1, C1 and RC1 have a narrow scheduling horizon. Hence only a few customers can be served by the same vehicle. Conversely, problem sets R2, C2 and RC2 have a large scheduling horizon, and more customers can be served by the same vehicle. The results are depicted in Table 1.

All algorithms in Table 1 are stochastic and they are implemented using Java-language. The objective is to minimize the total travelled distance. As can be seen from Table 1, our approach gave results very similar to the best results found in the literature. In addition it has made a major advantage that it provides the answer in a very short time which is highly demanded in cases of emergency.

Table 1. Comparison of results obtained by our approach with Ant Colony Optimization algorithm (AC) and Tabu Search algorithm (TS)

	AC	TS	Our approach
C1	828.38	828.38	828.65
C2	589.86	586.89	643.94
R1	1217.73	1210.14	1235.82
R2	967.75	969.57	970.55
RC1	1382.42	1389.78	1412.32
RC2	1129.19	1134.52	1143.56

7. CONCLUSION

In this paper, we presented an approach to resolve a dynamic vehicle routing problem with time windows. We started by modeling the problem. Then we presented the main operations of genetic algorithm with emphasis on methods used in our approach. After, we presented the model agent. Finally we have proposed an approach to solve the dynamic part of the problem.

REFERENCES

Bouamama S. and Ghedira K., (2005). OPT-D3G2A : Un nouvel Algorithme Génétique Distribué Doublement Guidé. *Revue électronique des sciences et technologies de l'automatique E-STA*, Volume 2 N°4.

Boudali I., Fki W. and Ghedira K., (2005). An interactive distributed approach for the VRP with time window. *Journal of Simulation Systems, Science and Technology*.

Coello C.A., (2001). A Short Tutorial on Evolutionary Multiobjective Optimization. *Proceeding of the 1st International Conference on Evolutionary Multi-Criterion Optimization, EMO.* Lecture Notes in Computer Science, vol.1993, pp. 21-40, Springer, Zurich, Switzerland.

Cordeau J.F., Laporte G. and Alain Mercier A., (2000) Unified tabu search heuristic for vehicle routing problems with time windows. *Publication CRT*. University of Montreal, Montreal, Canada.

Cordeau J.F, Desaulniers G., Desrosiers J., Solomon M. and Soumis F., (2000). The VRP with Time Windows. *Les cahiers du GERAD*.

Dantzig G.B. and Ramser J.H., (1959). The Truck dispatching problem. *Institute for Operations Research and the Management Sciences* Vol 6 N°1 PP 80-91.

Elfazziki A., Nejeoui A. and Sadgal M., (2005). Une Approche multi-agents pour la modélisation et l'optimisation des Systèmes de gestion de transport maritime, *RIST* Vol.15 N°01-02.

Fisher M.,(1995). Vehicle routing, *Handbooks of Operations Research and Management Science.* Chapter 1-8 pp. 1-31.

Gambardella L.M., Taillard E. And Agazzi G., (1999). MACS-VRPTW: a multiple ant colony system for vehicle routing problems with time windows. In *New Ideas in Optimization*, pages 63--76, McGraw-Hill, London.

Goldberg D.E., (1989). Genetic algorithms in search, optimization, and machine learning, *Advison-Wesley*.

Holland J., (1975). Adaptation in natural and artificial systems. University of Michigan Press, *Ann Arbor, Canberra ACT 2601*. Australia.

Jacques Ferber J., (1995). Les systèmes multi-agents : Vers une intelligence collective*, Inter-Editions.*

Kenneth A. De Jong. An analysis of the behavior of a class of genetic adaptive systems. Ph.D. Dissertation, University of Michigan, U.S.A, 1975.

LARSEN L., (2000). The dynamic vehicle routing problem. LYNGBY, *IMMPHD*, Denmark.

Nabaa M., Zeddini B. and Tranouez P., (2007). Approche décentralisée pour résoudre le problème du transport à la demande, *MajecSTIC.*

Zeddini B. and Zargayouna M., (2009). Auto-organisation spatio-temporelle pour le VRPTW dynamique. *RJCIA.*

Zhenggang D.C. and ZHENG L., (2009). Improved Multi-Agent System for the Vehicle Routing Problem with Time Windows. *TSINGHUA SCIENCE AND TECHNOLOGY* ISSNll1007-0214ll18/18llpp407-412 Volume 14, Number 3.