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Dynamic Vehicle Routing Problem for Medical Emergency Management

Jean-Charles Créput[1], Amir Hajjam[1],
Abderrafiãa Koukam[1] and Olivier Kuhn[2,3]
[1]*Systems and Transportation Laboratory, U.T.B.M., 90010 Belfort Cedex,*
[2]*Université Lyon 1, LIRIS, UMR5205, F-69622 Villeurbanne,*
[3]*Université de Lyon, CNRS*
France

1. Introduction

Nowadays telemedicine applications are more and more present in the state-of-the-art medicine. Telemedicine is a good way to improve access to healthcare, quality of care, reduce isolation and also costs. In that way we can now safely perform surgery between two places separated by several thousand km, navigate in 3D models of blood vessels or generate 3D models from Nuclear-Magnetic Resonance Imaging (MRI). But there is currently a lack of tools for all day medical acts which could improve medical system efficiency especially for medical emergency services.

In order to help medical emergency services, the project MERCURE (Mobile and Network for the Private clinic, the Urgency or the External Residence) has been launched in order to create tools that optimize, follow and manage emergency interventions. The current problem is that the choice of the doctor for a patient is done by hand.The call center is neither aware of the exact location nor the current state of the doctors. Thus it is rarely the best located doctor who is chosen and moreover he may not have correct equipments to heal the patient. To optimize that aspect, we have developed software allowing the optimized management of human and material medical resources.

This problem, conventionally called vehicle routing problem (VRP), is one of the most widely studied problems in combinatorial optimization. In the standard VRP, a fleet of vehicles must be routed to visit a set of customers at minimum cost, subject to vehicle capacity constraint and route duration constraint. In the static version of the problem, it is assumed that all customers are known in advance to the planning process. In the case of medical emergency management, it includes some dynamic elements. The information data often tends to be uncertain or even unknown at the time of the planning. It may be the case that patients, driving times or service times, are unknown before the day of operation has begun, but become available in real-time. Due to the recent advances in information and communication technologies, such as geographic information systems (GIS), global positioning systems (GPS) and mobile phones, companies are now able to manage vehicle routes in real-time. Hence, with the increased access to these services, the need for robust real-time optimization procedures will be of critical importance, for small to big distribution companies, whose logistics are based on a high reactivity to the customer demand.

As for static vehicle routing problems, a lot of versions of the dynamic problem exist depending on application areas. For an overview and classification of the numerous versions of real-time routing and dispatching problems, we refer the reader to the general surveys and classifications given in (Ghiani & al., 2003), (Larsen, 2000), (Larsen &al., 2008), (Gendreau &Potvin, 1998) and (Psaraftis, 1995), (Psaraftis, 1998). One of the simplest versions is the standard dynamic VRP with capacity and time duration constraints (Kilby & al., 1998), called "dynamic VRP" in this paper, which is a straightforward extension of the classical static VRP (Christofides & al., 1979). In this problem, the customers are the only elements which have a dependence on time. Customers are not known in advance but arrive as the day progresse. The system has to incorporate them into the already designed routes in real time. Problems fitting this model appear frequently in industry.
A lot of different versions of the dynamic VRP have been studied, whereas very few dynamic routing problems except the dynamic VRPTW or dynamic PDPTW are recognized as standard problems well suited to allow comparative evaluations of heuristics and metaheuristics on a common set of benchmarks. For example, only two papers on the dynamic VRP that shared detailed results on a common test set have been found. They are first an adaptation of the ant colony approach MACS-VRPTW Gambardella & al., 1999) by (Montemanni & al., 2005), and second a genetic algorithm (Goncalves & al., 2007). They share results (Kilby & al., 1998), test set with 22 problems of sizes from 50 with up to 385 customers. This paper tries to go one step further in that direction considering the dynamic VRP as a standard dynamic problem, and yielding a comparative study with these two methods on the Kilby et al. test set. Then, we restrict the scope of our work to the dynamic VRP, with capacity and time duration constraints.
In the following section, the MERCURE project will be presented. In section 3 we shall introduce our optimization system with implementation details. Then, section 4 reports experiments carried out on the Kilby at al. benchmark and the comparisons made with a state-of-the-art ant colony approach and a genetic algorithm already studied on these benchmarks. Finally, last section is devoted to the conclusion and further research.

2. Project MERCURE

2.1 Aim of the project

The project MERCURE takes part in the French pole of competitiveness therapeutic innovations. The aim of the project is to give, thanks to information technologies, an optimized and dynamic management of resources used in the scope of urgentist interventions like material and human resources. The system gives a real-time tracking of current interventions, from the reception of the call to the closure of the medical record. It optimizes resources, travel times and takes care of whole constraints relative to the domain: emergency level, pathology, medical competences, location and other specific aspects related to this profession.
The platform exploits satellite location system associated with a geographical information system (GIS) and is based on results coming from works on vehicle routing problems (Creput & al., 2007). With present technologies we can have accurate current location of patients and doctors via GIS and A-GPS1 respectively. The A-GPS system has 3 main uses.

1. Know the position of each medical team.
2. Help the doctor to reach quickly the intervention point.
3. Track in real-time medical teams and resources.

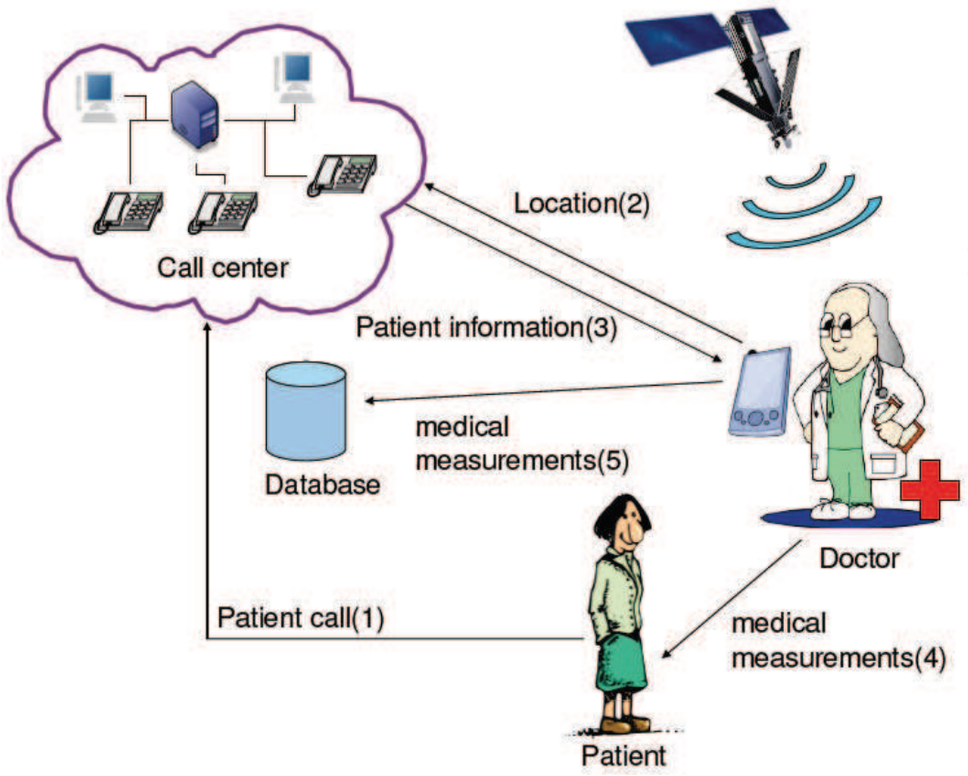

Fig. 1. Data exchanges after a patient call

Here is a basic scenario when an emergency call arrives (see figure 1). Call center point of view:

- Information about the patient (name, address, pathology…) is inputted in the software.
- Patient's information are processed, a set of doctors which suit to the patient's needs is created (depending of the pathology, the intervention area…).
- The selection of a doctor in the previously created set is done via an optimization algorithm. Here we focus on optimizing several criteria like distance, reaction time. . . The patient is inserted in the doctor's road.
- The selected doctor is warned by a message on his PDA2.

Now from a doctor point of view:

- The doctor receives a patient request on his PDA and he is geo-guided to the patient's location via A-GPS.
- As soon as he arrives, all information about the patient are shown: previous diseases, his allergy, current treatments. . . Those information are transferred from the database via radio link like GPRS3 or UMTS4 for example.
- When the auscultation is finished, he inputs results and notes that are immediately transferred to the central database. Then he goes on with the next patient.

2.2 Improvements

This whole process improves reaction time of emergency services and thus save lives. It also provides an unique database gathering up-to-date information about patients and so facilitate the follow-up of patients. Another main improvement is that the answer fits to the

patient's needs. In other words, the call is answered by a doctor-regulator who is able to help the patient to describe and specify his illness. This is a real telemedicine act and thus the software is able to select the appropriate doctor or send an ambulance. Moreover this system may suit to other emergency services like fire brigade or police department with some adaptations. There are some papers about ambulances location and relocation models written by (Gendreau & al., 1997), (Gendreau & al., 1999), (Gendreau & al., 2001) and (Brotcorne & al., 2003). But currently we are not aware of other tools for such size of emergency services. This project is realizable thanks to recent new technologies like A-GPS, wireless data communication and improvements in artificial intelligence and operations research for dynamic problems.

3. Dynamic optimization system for urgentist

In the MERCURE project, we are in charge of the optimization part for the selection of doctors and assignment of patients. We have tackled this problem as an operations research problem named Vehicle Routing Problem (VRP) (Toth & Vigo, 2001).

3.1 Problem statement

Allan Larsen stated in his PhD report (Larsen, 2000) that emergency services have 2 major criteria (see figure 2):

- They are highly dynamic: most or all requests are unknown at the beginning and we have no information about their arrival time.
- The response time must be very low because lives can be in danger.

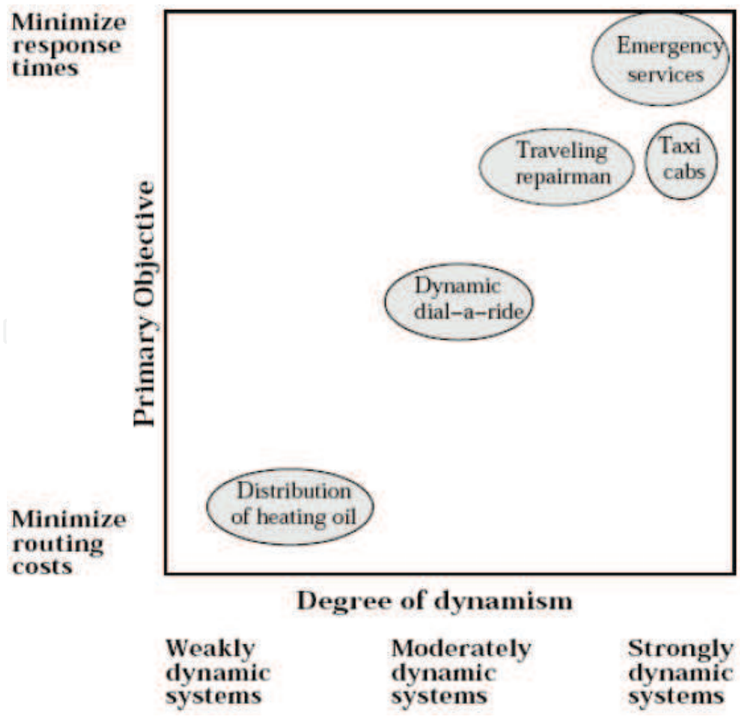

Fig. 2. Framework for classifying dynamic routing problems by their degree of dynamism and their objective

That is why we have chosen to represent the emergency problem as a Dynamic Vehicle Routing Problem with Time Window (DVRPTW) which is presented in the next paragraph. This extension of the well known VRP suits very well to this kind of problem because it takes care of the 2 criteria previously stated. Time windows are perfect to consider response time and the dynamic aspect allows the system to receive requests during the optimization process.

1) DVRPTW presentation: A Dynamic Vehicle Routing Problem with Time Windows is a specialization of the well known Vehicle Routing Problem. The static VRP is defined on a set $V = \{v_0, v_1, ..., v_N\}$ of vertices, where vertex v_0 is a depot at which are based m identical vehicles of capacity Q, while the remaining N vertices represent customers, also called requests, orders or demands. A non-negative cost, or travel time, is defined for each edge $(v_i, v_j) \in V \times V$. Each customer has a non-negative load $q(v_i)$ and a non-negative service time $s(v_i)$. A vehicle route is a circuit on vertices. The VRP consists of designing a set of m vehicle routes of least total cost, each starting and ending at the depot, such that each customer is visited exactly once by a vehicle, the total demand of any route does not exceed Q, and the total duration of any route does not exceed a preset bound T (see figure 3).

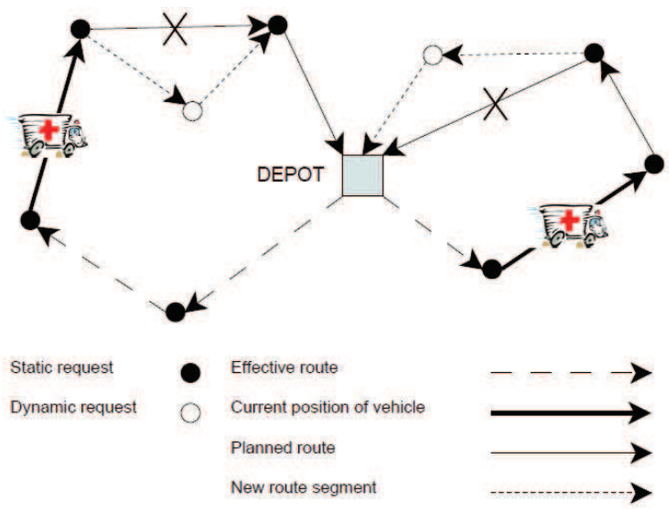

Fig. 3. Example of dynamic vehicle routing problem with 7 static requests and 2 immediate requests

As it is the mostly done in practice (Cordeau & al., 2005), we address the Euclidean VRP where each vertex v_i has a location in the plane, and where the travel cost is given by the Euclidean distance $d(v_i, v_j)$ for each edge $(v_i, v_j) \in V \times V$. Then, the objective for the static problem is the total route length (*Length*) defined by

$$Length = \sum_{i=1,..,m} \left(\sum_{j=1,...,k_i-1} d\left(v_j^i, v_{j+1}^i\right) + d\left(v_0, v_1^i\right) + d\left(v_{k_i}^i, v_0\right) \right) \quad (1)$$

where $v_j^i \in V$, $0 \le j \le k_i$, $0 \le k_i \le N$, are the ordered set of demands served by the vehicle i, $1 \le i \le m$, *i.e.* the vehicle route. The capacity constraint is defined by

$$\sum_{j=1,...,k_i} q\left(v_j^i\right) \le Q, \; i \in \{1,...,m\} \quad (2)$$

then, assuming without loss of generality that the vehicle speed has value 1 the time duration constraint is given by

$$\sum_{j=1,\ldots,k_i} s\left(v_j^i\right) + \sum_{j=1,\ldots,k_i-1} d\left(v_j^i, v_{j+1}^i\right) + d\left(v_0, v_1^i\right) + d\left(v_{k_i}^i, v_0\right) \le T \ , \ i \in \{1,\ldots,m\} \tag{3}$$

The problem is NP-hard. Thus, using heuristics is encouraged in that they have statistical or empirical guaranty to find good solutions for large scale problems with several hundreds of customers. For example, the most powerful Operations Research (OR) heuristics for the VRP, referred in the extensive surveys (Gendreau & al., 2002), (Cordeau & al., 2005), are based on metaheuristic frameworks as the Tabu Search, simulated annealing, and population based methods, such as evolutionary algorithms, adaptive memory and ant algorithms. Other methods can hybridize several metaheuristics principles, such as for example the very powerful active guided local search (Mester & Bräysy, 2005), which is maybe the overall winner approach considering both quality solution and computation time.

In the static VRP, vehicles must be routed to visit a set of customers at minimum cost, assuming that all orders for all customers are known in advance. However, in the dynamic VRP, new tasks enter the system and must be incorporated into the vehicle schedules and served as the day progresses. In real-time distribution systems, demands arrive randomly in time and the dispatching of vehicles is a continuous process of collecting demands, forming and optimizing tours, and dispatching requests to vehicles in order to process requests at the required geographic locations. In the case of the static VRP, the three phases of demands reception, routes optimization and vehicles travelling are clearly separated and sequentially performed, the output of a given phase being the input of the subsequent one. At the opposite, we can see the dynamic VRP as an extension of the static VRP where these three time-dependent processes are merged into an approximately same period of time. This period of time is called the working day or planning horizon of length D. Here, we precisely define the working day length D as the length of the collecting period, knowing that the optimization period and the vehicle travelling period would have to be of approximately the same length.

It is often the case that in real life situations the objective function consists of a trade-off between travel costs and customer waiting time *i.e.* the delay between the occurrence time of a demand and the instant the service of the demand begins, often called system response time in the literature. Hence, we define the dynamic VRP as a bi-objective problem by adding to the classical objective and constraints of the standard VRP a supplementary objective which consists of minimizing the average customer waiting time. In a dynamic setting the waiting time can be more or less important depending on the application at hand. Examples of applications where the waiting time is the important factor include the replenishment of stocks in a manufacturing context, the management of taxi cabs, the dispatch of emergency services, geographically dispersed failures to be serviced by a mobile repairman. It is then necessary to identify the many trade-offs between these two objectives. Hence, to gauge the reactivity and the dynamism of the system, a real-time objective consists in minimizing the average customer waiting time (WT) :

$$WT = \sum_{i \in \{1,\ldots,N\}} W_i \Big/ N \tag{4}$$

where W_i is the waiting time of demand i, *i.e.* $W_i = st_i - t_i$ where $t_i \in [0, D]$ is the demand occurrence time, and st_i is the time when the service starts for that demand.

It is worth noting that the total route length and the classical constraints of capacity and time duration are evaluated exactly the same way as for the static problem case. This is done in order to be the closest as possible to the standard problem formulation and to allow comparisons between the solutions generated in both the dynamic and static cases. Hence, a route remains a simple schedule of demands. Whereas, in order to evaluate the customer waiting time we need to consider travel distances and service times, but also consider the "real time" at which the service is really performed, thus taking care of the possible extra times during which the vehicle may be waiting, or driving back to the depot before some new requests are dispatched to it. It should be noted also that we assume that no information is available about the future locations of the demands.

Also, it may be possible that a vehicle will finish its work and go back to the depot after the period D has finished. Hence, in order to gauge what is the real part of the services that are performed within the working day in real-time or after the day has finished once all demands are already known, it may be useful to compute an auxiliary criterion that we define as the real finishing time of the vehicle services, *i.e.* the date when all the vehicles have finished their service and have returned to the depot. In this way, looking both at the vehicle lengths and at the finishing time will give another intuitive light about the dynamicity of the system. Thus, we define the maximum vehicle finishing time (MT) as

$$MT = \underset{k\in\{1,\ldots,m\}}{Max} \{FT_k\} \tag{5}$$

where FT_k is the vehicle finishing time of vehicle k, that is, the occurrence time at which the vehicle arrives to the depot once it has served its last customer for the day. We will see that this finishing time can be maintain in adequate bounds even when introducing some delay to the departure of the vehicles, thus drastically and simultaneously reducing the total route length.

Clearly, only the evaluations of equations (4) and (5) depend on a real-time realization, whereas the evaluations of (1)-(3) only depend on the scheduling of the demands the same way as for the standard VRP. Then, to empirically evaluate a given real-time optimization approach, we need to embed its execution in a real-time simulator.

Between a VRP and a DVRPTW, 2 constraints are added:

- Usually, relevant information, such as new patient requests and cancelled requests can occur all the time, even after the optimization process has started. The dynamism consists in receiving several requests during the evolution of the simulation. These dynamic variations can be very important to really reduce the costs in vehicle routing problems. The date when the request i arrives is noted g_i as the generation date of request i.
- The time windows constraint which consists in having 2 time limits associated with each request i: $[a_i, b_i]$. The vehicle must start the customer service before b_i, but if any of them arrives at customer i before a_i, it must wait. So the smaller the time window of a request is the harder will it be to find a good insertion place in a vehicle road.

To these 2 constraints, a third one can be added depending of the instance of the problem. It comes from the fact that all doctors may not start from the same location so we must manage multi-depots instances of DVRPTW.

2) Matching to DVRPTW: We have to affect each real entity (call center, resources and patients) to one in routing problem which are vehicles, requests and the company. The most

logical way to make them correspond is to match the doctors to the vehicles, the patients to the requests and the call center to the company.
But there is some specificity that we must consider in the problem.
First the patient may need a specialist for his illness. So not all vehicles can serve this request. It is the same thing for ambulances. In the same way, we must avoid sending a woman into a district with bad reputation. We need to have in our application different types of vehicle which is not managed in classical VRP instances where all vehicles are identical. So in our DOS a request can be dedicated to a vehicle and only this vehicle can serve it.
We must also take care of the loading of the system. We have a time constraint that is specific to emergency services. In classical VRPTW, when some requests are not served at the end of the day they are deferred to the next day. Here when the system is overloaded, we must serve most urgent requests and redirect less urgent ones to a classical doctor if possible.

3.2 Dynamic optimization system

In order to solve DVRPTW, we have developed a simulator that we have called Dynamic Optimization System (DOS). You can find some screenshots in figure 4.

Fig. 4. Evolution of a simulation in DOS on a static benchmark. Dotted lines represent the road segments that have been completed

1. Architecture of the simulator: This simulator is divided in 2 distinct parts.

On the one hand we have a multi-agents simulator. Its role is to schedule main entities present in a VRP. Each entity is represented by a process.

- The environment process is dedicated to generate events during the simulation.
- The company process simulates a real company. It receives requests and plans vehicles roads.
- Vehicles processes follow roads given by the company and serve requests.

All these processes are synchronized on a same clock owned by the scheduler so they advance in time simultaneously. One simulation step lasts *To* milliseconds in real time and the corresponding simulation time depends on a ratio to suit the problem. As our application domain is in real time, the ratio will be 1. So each step will last *To* millisecond in the simulation.
During a step, each process is called once to make a short action and so share CPU time as shown in figure 5. Actions that need a lot of time must be divided in several shorter actions with small execution time.

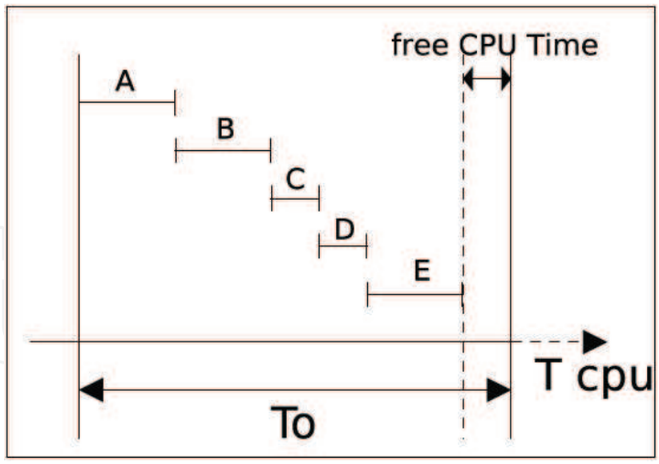

Fig. 5. CPU sharing between 5 processes (A to E) during To ms

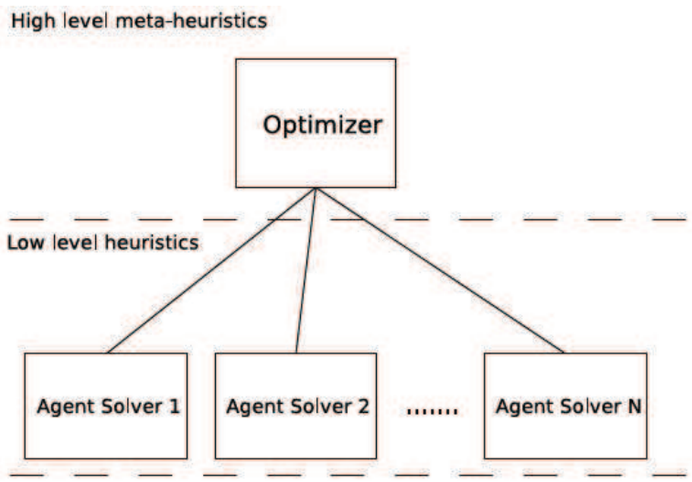

Fig. 6. Architecture of the optimization part of the simulator

One the other hand we have the optimization part.
The optimization process can be viewed as a black box, receiving the current solution (a set of vehicles) and the known requests and giving back a better solution if possible. This part of our DOS is explained more precisely in 4. The company has the role of asking the optimizer to optimize current solution. After a fixed time, the company reads the solution and gives new plans to the vehicles or confirms the current one. The exchanges between the two parts are done via a letterbox with exclusive access. This ensures the data transfers between two unsynchronized threads and prevents data overriding.

2. Additional features: Through this system we can also gather lots of interesting information that can be processed in order to extract some statistical data. We can imagine optimizing the number of doctors depending of the date, the specialization the most needed and so on. Once enough requests are stored in the database, we can extract main trends and optimize human and logistic resources.

Moreover we can use that probabilistic information on future events to route doctors to their next patient by making them pass close to area with high probability of new requests.

(Bertsimas & al., 1990) describe this kind of problems and call them Probabilistic Vehicle Routing Problem (PVRP).

4. Optimization approach

We are now facing a DVRPTW that we must solve relatively quickly in order to be able to warn doctors of a new patient to see urgently. In a VRP problem, finding one of the best solutions requires a lot of time. Here we prefer having a relatively good solution quickly and then improve it.
To do that, our optimizer has a 2-level architecture. The top level uses a global meta-heuristic strategy and controls several solver agents. In the lower level we can find previously mentioned solver agents which represent different heuristics for solving VRP (see figure 6).

A. Global Meta-heuristic

This level aims at finding the best solution by using several solver agents. Each of these agents represents a heuristic for solving VRP (see 4-B). That can be seen as a worker with different tools (the solver agents) at his disposal for doing his job, here optimizing vehicles routes. It has to choose the strategy which suits the best to the problem for example creating the first solution. To do that, the optimizer initializes a set of selected solver agents and tells them to do the job separately. Then before a defined generation time (Tg) it gathers all solutions from the agents and makes a selection to keep most interesting ones depending on the strategy and then gives the best solution to the company via the letterbox. So we manage a population of solution where we keep or replace individuals like in genetic algorithms. This allows exchanging solutions between different heuristics and so discovering new ones and getting out local optima.
The solver agents are scheduled by the optimizer like the processes in the simulation part. When all used solver agents have been activated once, one step is done. So we can have several different optimization methods in parallel. The specifics of our solver agents are approached in the next part.

B. Low-level heuristics

We shall now analyze the lower level where solver agents are located. Their aim is to solve a type of VRP thanks to a specified heuristic. Each agent uses one or more heuristics which can be very basic like a 2-opt which consists in exchanging 2 roads (see figure 7) or more complicated like neural networks or other artificial intelligence methods. The optimizer is aware of features of all solver agents.

1. **Memetic SOM:** The main optimization algorithm we are using is based on local search (Rochas & Taillard, 1995) and selforganizing maps (SOM) (Kohonen, 24), (Ghaziri, 1996), (Modares & al., 1999), by embedding them into an evolutionary algorithm. This approach is called memetic SOM (Creput & al., 2007).

One way to explain the "philosophy" of the approach may be by referring the reader to some well known concepts in the Artificial Intelligence domain like emergent computation, bio-inspired methods, and soft-computing concepts including neural network, evolutionary algorithms, or hybrid systems. The approach can be seen as following a biologic metaphor where customers constitute external stimuli to which a "biologic organism", may respond dynamically adapting its shape continuously to absorb, neutralize or satisfy the external

stimuli. More generally, we can exploit this metaphor to address a large class of spatially distributed problems of terrestrial transportation and telecommunications, such as facility location problems, vehicle routing problems or dimensioning mobile communication networks (Creput & al., 2005), (Creput & Koukam, 2007). These problems involve the distribution of a set of entities over an area (the demand) and a set of physical systems (the suppliers) which have to respond optimally relatively to the demand. This optimal response constitutes the solution to the optimization problem. Thus, a distributed bio-inspired heuristic to address such problems is a simulation process of such spatially distributed entities (vehicles, antenna, customers) interacting in an environment which produces the "emergence" of a solution by the many local and distributed interactions

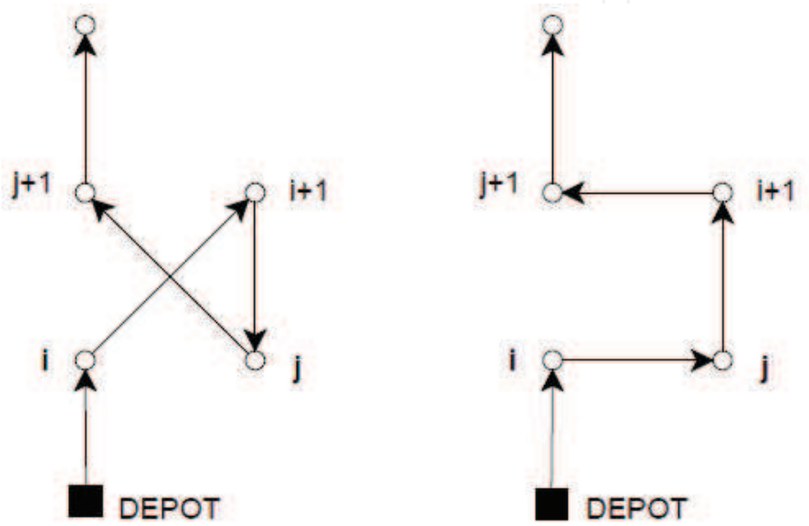

Fig. 7. Example of a 2-opt operation

Here, we generalize the SOM algorithm giving rise to a class of "closest point findings" based operators that are embedded into a population based metaheuristic framework. The structure of the metaheuristic is similar to the memetic algorithm, which is an evolutionary algorithm incorporating a local search (Moscato & Cotta, 2003). The SOM is a (long) stochastic gradient descent performed during the many generations allowed, and used as a "local search" similarly as in a classical memetic algorithm. This is why the approach has been called memetic SOM (Moscato & Cotta, 2003) in previous work and we will maintain the name in this paper. The approach follows two types of metaphors. It follows a self-organization metaphor at the level of the interacting problem components, or heuristic level, and an evolution based metaphor at the population based metaheuristic level. Since demands are conceptually separated from the routes representation, which is an independent network or graph in the plane which continuously adjusts itself to the data, this leads to a straightforward application from a static to a dynamic setting. As they arrive, new demands are simply inserted on-line in a buffer of demands, in constant time, leading to a very weak impact on the course of the optimization process.

The evolutionary algorithm embedding SOM is based on memetic loop which applies at each iteration (called a generation) a set of operators to a population of individuals. The construction loop starts its execution with solutions having randomly generated vertex

coordinates, into a rectangle area containing cities. The improvement loop starts with the single best previously constructed solution, which is duplicated in the new population. The main operator is the SOM algorithm applied to the graph network. At each generation, a predefined number of SOM basic iterations are performed letting the decreasing run being interrupted and combined with application of other operators, which can be other SOM operators with their own parameters, mapping and fitness evaluation, and selection. Each operator is applied with probability prob. Details of operators are the followings:

1. Self-organizing map operator. It is the standard SOM applied to the ring network. One or more instances of the operator can be combined with their own parameter values. A SOM operator is executed performing η_{iter} basic iterations by individual, at each generation.
2. SOM derived operators. Two problem specific operators are derived from the SOM algorithm structure for dealing with the VRP especially. The first, denoted SOM VRP, is like a standard SOM but restricted to be applied on a randomly chosen vehicle, using requests already assigned to that vehicle. While capacity constraint will be considered in the mapping operator below, a SOM based operator, denoted SOM DVRP, deals with the time duration constraint. It performs a greedy insertion move.
3. Fitness/assignment operator. This operator, denoted FITNESS, generates a VRP solution and modifies the shape of the ring accordingly. The operators greedily maps customers to their nearest neuron, considering only the neurons not already assigned to a customer, and where vehicle capacity constraint is satisfied. The capacity constraint is then greedily tackled through the requests assignment. Once the assignment of requests to routes has been performed for each individual this operator evaluates a scalar fitness value that has to be maximized and which is used by the selection operator. Taking care of time duration constraint the fitness value is computed sequentially following routes one by one and removing a request from the route assignment if it leads to a violation of the time duration constraint.
4. Selection operators. Based on fitness maximization, the operator denoted SELECT replaces worst individuals, which have the lowest fitness values in the population, by the same number of bests individuals, which have the highest fitness values in the population.

The memetic SOM is very interesting because of its adaptability and flexibility due to its neighbourhood search capabilities and simple moves performed in the plane. We can easily add or remove requests without having to relaunch an optimization from the beginning because they are immediately inserted at a good position.

We are currently working on the integration of this algorithm in the optimization system.

2. **Classical optimizations:** Moreover we agentified several classical optimization heuristics to make them work in our multi-agents optimization architecture. We have chosen some intra-route and inter-route heuristics like 2-opt (see figure 7) or 1-1 exchange (see figure 8), to improve solutions obtained by memetic SOM and also explore new solutions by mutating some of them.
3. **Similar approach:** Our approach is similar to that of (Kytjoki & al., 2007) called variable neighbourhood search (VNS) where they create an initial solution by a cheapest insertion heuristic that is improved with a set of improvement heuristic. In a second phase they improve the solution with the same set of heuristic until there are no more improvements. With this approach they can solve very large scale VRP, up to 20,000

customers within reasonable CPU times. But their solution does not address time windows VRP and was not tested on dynamic sets.

We also think that the mixing of artificial intelligence approach with several operations research approaches can give better results than focusing on a unique one. That is why we have chosen such architecture for the optimization part to be able to add different methods and see which ones work well together.

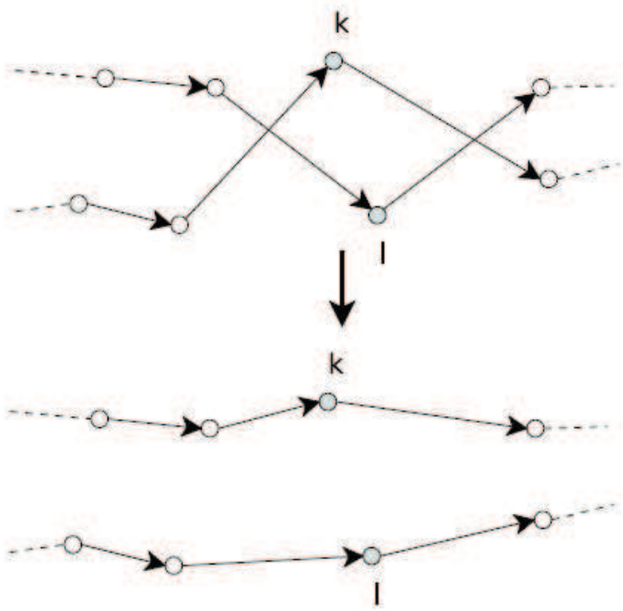

Fig. 8. Example of 1-1 exchange move

5. Experimentation

In this section, we will present an analysis of the trade-off between length optimization and customer waiting time as a function of different degrees of dynamism of the optimization system, and will report results for a benchmark test set for which some already performed experiments exist, even if partials and incomplete. Results reported in the literature and examined in this paper were also obtained considering a medium degree of dynamism, but by modifying the instance by hand, by treating demands with an available time after the half of the day as if they arrived the day before. We prefer in this paper to operate by delaying vehicle starts, in order to report the control of dynamism to the optimization system, rather than to the different ways of managing and using the benchmark test set. In that way, we emphasize to the logical continuity that arises from the dynamic case problem to the static case problem, the latter being a particular case of the former with vehicle delay starts exceeding the working day. In other words, we consider the degree of dynamism as a property of the optimization system, rather than of instances, in order to discriminate algorithms and not the instances.

It is worth noting that at the moment of writing this paper very few approaches to the dynamic VRP were found sharing experiments on a same benchmark. The dynamic problems adopted in this paper are the only set of benchmarks for the dynamic VRP we

have found in the literature on which some metaheuristic approaches are effectively evaluated, that is, the 22 test problems originally proposed by (Kilby & al., 1998).
The proposed memetic SOM was programmed in Java and has been ran on a AMD Athlon 2 GHz computer. All the tests performed with the memetic SOM are done on a basis of 10 runs per instance. For each test case is evaluated the percentage deviation, denoted "%*Length*", to the best known route length, of the mean solution value obtained, *i.e.*

$$\%Length = (\text{mean } Length - Length^*) \times 100 / Length^* \tag{8}$$

where *Length** is the best known value taken from the VRP Web, and "mean Length" is the sample mean based on 10 runs. The average computation times are also reported based on 10 runs. The average customer waiting tine (4) and the maximum vehicle finishing time (5) are expressed as a fraction of the working day in order to compare data with different working days. The waiting time is expressed as a percentage of the working day length *D* by

$$\%WT = \text{mean } WT \times 100 / D, \tag{9}$$

whereas, the maximum finishing time is expressed as an excess deviation to the working day by

$$\%MT = (\text{mean } MT - D) \times 100 / D. \tag{10}$$

While originally, Kilby et al. have set the number of vehicles to 50 for each problem, we prefer to set the number of vehicles according to the overall load of each problem. We think that it looks reasonable to not over-dimension the vehicle resources since it is generally the case in concrete situations that a limited amount of resources are available. Hence the maximum number of vehicles *m* available to perform the tasks for a given problem is set to

$$m = \sum_{i=1,\ldots,N} q(v_i)/Q + 0.1\left(\sum_{i=1,\ldots,N} q(v_i)/Q \right), \tag{11}$$

with $q(v_i)$ the load of demand v_i and Q the vehicle capacity.
This setting also guarantees that it is possible to serve all the demands for the problems considered. Finally, to make things concrete and realistic, the vehicle speed defined in the benchmarks of 1 distance-unit by 1 time-unit can be seen as a vehicle speed of 1 km/mn, or equivalently of 60 km/h. In order to be concrete, we will express the real-time in minutes and the distances in km when reported by their absolute values in some graphics. The working days are roughly between 4 hours to 17 hours, with an exception of a single test case having a 195 hours working day. It is worth noting that the parameter *N* and the total load of the demands are known before optimization in order to adequately dimension the system. Hence, the working day *D* can be decomposed into the many required time-slices. We assume that such values are necessarily known in advance in order to model a concrete real-life situation where a limited number of vehicles are intended to serve a maximum amount of demands, and to reasonably dimension the real-time simulator memory and the optimization system.
We report detailed results of the experiments performed on the (Kilby & al., 1998) benchmarks in Table 1. Here, such results are mainly given in order to allow further comparisons with heuristic algorithms for the dynamic VRP. In table 1, results are presented against the two other approaches found in the literature (Montemanni & al., 2005),

(Goncalves& al., 2007), that have used the benchmark set with a medium degree of dynamism, considering that half of the demands were known in advance. It is worth noting that we simulate the same degree of dynamism by a vehicle delay start time at $D/2$. As we argued along this paper, we consider the degree of dynamism as a property of the system rather than a property of the instance. The first column "Name-size" of the table indicates the name and size of the instance. The second column "D" indicates the working day length, and the third column the best known value obtained for the static problem. Then, results are given within five columns for a given algorithm configuration. The columns "%Length", "%WT", and "%MT" are respectively defined by equations (8), (9), and (10), as the percentage routes length, percentage average customer waiting time, and percentage maximum finishing time. The column "±%CI" is the 95% confidence interval for the routes length. Finally, the column "Sec" reports the computation times in seconds. Two algorithm configurations are considered respectively with fast (To=30ms) and long (To=200ms) computation times. The metaheuristic population size was set to Pop = 10.

When looking at the results of table 1, one should observe the different tradeoffs between route lengths (%*Length*) and waiting times (%*WT*). Then, a medium degree of dynamism will favor the drivers working period to be smaller, but at the expense of the customer waiting time. In the table 1, the approach is compared with an ant colony approach, that is, an adaptation of the well known MACS-VRPTW approach of (Gambardella & al., 1999) that is considered as one of the best performing approaches to the static VRP. The application to the dynamic VRP is due to (Montemanni & al., 2005). Also, it is compared with the genetic algorithm of (Goncalves & al., 2007).

Considering that materials used are quite similar, the memetic SOM yields a better solution quality than the two approaches for less computation time spent. In order to evaluate how the memetic SOM performance behaves as the computation time diminishes, we performed a supplementary set of experiments with a timer-clock at To = 20 ms. The memetic SOM clearly outperforms the ant colony approach in all cases, being roughly an hundred times faster. It also outperforms the genetic algorithm approach being roughly ten times faster. It is worth noting that none of the two approaches report the customer waiting times, this point being a clear drawback of the results presented in the two papers. The authors only claim that the experiments were done with a medium degree of dynamism, half of the demands being considered as known in advance. It is a goal of this paper to be more precise when evaluating a dynamic system, by explicitly considering the tradeoffs between the length and waiting time minimization, as well as the computation time spent.

6. Conclusion

The MERCURE project is helpful for emergency services by giving them appropriate tools to do their job in better conditions. By representing medical emergency services by a Dynamic Vehicle Routing Problem with Time Windows, we are able to optimize human and material resources and so reduce costs, reaction time and maybe save lives.

We have presented the dynamic VRP as a straightforward extension of the classic and standard VRP, and a hybrid heuristic approach to address the problem using a neural network procedure as a search process embedded into a population based evolutionary algorithm, called memetic SOM.

			memetic SOM (fast, start time D/2, Pop=10)					memetic SOM (long, start time D/2, Pop=10)					Montemanni et al. (2005)		Goncalves et al. (2007)	
Name-size-veh	D	Best	%Length	±%CI	Sec[a]	%WT	%MT	%Length	±%CI	Sec[a]	%WT	%MT	%Length	Sec[b]	%Length	Sec[c]
c50	351	524.61	18.58	2.48	16.52	45.49	50.37	17.82	2.14	110.82	46.45	55.19	30.00		13.99	
c75	346	835.26	24.59	2.88	17.00	39.59	56.99	22.65	2.20	106.01	39.53	50.58	24.75		15.89	
c100	399	826.14	14.33	2.68	18.44	42.14	47.69	13.39	2.06	118.60	42.13	46.12	29.03		24.07	
c100b	468	819.56	9.76	4.19	19.49	34.82	33.06	12.88	2.02	127.54	34.92	33.97	24.95		13.60	
c120	794	1042.11	9.47	2.22	29.33	29.26	18.11	7.95	2.62	189.07	29.32	17.12	46.34		37.22	
c150	399	1028.42	32.05	2.20	17.89	36.98	43.23	32.14	1.54	114.52	36.50	41.08	41.58		30.59	
c199	399	1291.29	33.23	1.72	17.22	35.71	37.89	30.29	2.18	113.69	35.35	40.05	42.88		30.18	
f71	211	237	30.89	3.99	9.73	48.76	47.20	27.03	2.94	63.19	49.07	47.01	47.26		19.41	
f134	11741	11620	53.14	8.37	48.38	18.12	18.60	46.98	5.34	318.72	18.59	20.21	38.42		35.29	
tai75a	769	1618.36	19.99	3.02	17.10	31.41	42.08	15.40	2.07	108.87	31.21	39.17	20.18		15.18	
tai75b	905	1344.62	23.93	4.01	18.76	30.75	32.49	22.54	3.69	123.42	31.07	34.08	26.73		13.86	
tai75c	782	1291.01	20.67	2.93	16.72	34.55	36.57	21.93	2.68	108.63	34.70	36.55	28.12		25.64	
tai75d	789	1365.42	17.26	2.94	17.13	33.10	38.71	14.89	3.28	112.53	33.54	40.20	11.98		10.22	
tai100a	897	2041.34	15.98	3.67	40.12	36.97	43.04	13.40	2.21	262.21	37.35	43.81	18.94		18.65	
tai100b	799	1940.61	17.13	2.78	36.35	39.01	45.48	15.19	2.13	239.28	39.05	47.32	20.99		15.48	
tai100c	905	1406.2	23.39	2.99	34.92	25.74	23.38	24.58	3.11	229.39	26.44	24.69	17.76		24.02	
tai100d	782	1581.25	28.21	2.73	33.90	31.78	38.61	24.71	3.68	221.12	31.75	39.09	30.34		20.66	
tai150a	1062	3055.23	19.75	2.52	44.73	34.89	34.71	20.72	3.05	291.58	34.70	35.08	25.69		20.51	
tai150b	988	2656.47	21.36	3.22	38.83	32.79	25.69	20.89	2.38	254.67	32.69	26.81	25.24		24.49	
tai150c	1081	2341.84	21.30	1.44	42.40	27.87	25.40	18.61	2.01	277.16	27.53	26.14	28.79		24.43	
tai150d	1025	2645.39	20.16	3.06	40.44	35.30	26.15	16.22	1.87	269.60	35.20	29.40	21.12		20.55	
tai385	4816	24431.44	38.03	2.21	95.76	29.33	27.03	38.86	1.65	623.00	28.64	27.33	-		-	
Average without tai385			**22.63**	0.63	**27.40**	34.52	36.45	**19.82**	0.53	**179.08**	34.62	36.84	28.62	1500	21.62	1500
Average all			23.33	0.66	30.51	34.29	36.02	20.58	0.51	199.26	34.35	36.41				

[a] Time per run in AMD Athlon (2 GHz) seconds, Java program.
[b] Time per run in Pentium IV (1.5 GHz) seconds, C program.
[c] Time per run in Pentium IV (2.4 GHz) seconds, Java program.

Table 1. Comparative evaluation on the 22 instances of Kilby et al (1998) with medium dynamism

The results given by our simulator look encouraging in that the approach clearly outperforms the few heuristic approaches already applied to the dynamic VRP and evaluated in an empirical way on a common benchmark set. We claim that the memetic SOM is simple to understand and implement, as well as flexible in that it can be applied from a static to a dynamic setting with slight modifications. Also, we think that the memetic SOM is a good candidate for parallel and distributed implementations at different levels, at the level of the population based metaheuristic and at the level of the cellular partition of the plane.
Another interesting aspect of our simulator is that it currently focuses on medical emergency services but it could be extended to address several kinds of emergency services problems.

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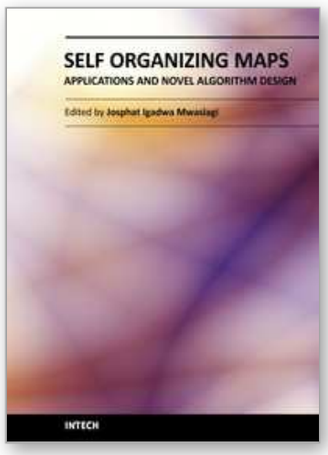

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Kohonen Self Organizing Maps (SOM) has found application in practical all fields, especially those which tend to handle high dimensional data. SOM can be used for the clustering of genes in the medical field, the study of multi-media and web based contents and in the transportation industry, just to name a few. Apart from the aforementioned areas this book also covers the study of complex data found in meteorological and remotely sensed images acquired using satellite sensing. Data management and envelopment analysis has also been covered. The application of SOM in mechanical and manufacturing engineering forms another important area of this book. The final section of this book, addresses the design and application of novel variants of SOM algorithms.

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University Campus STeP Ri
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