Improvement of drug delivery routes through the adoption of multi-operator evolutionary algorithms and intelligent vans capable of reporting real time incidents

***Abstract*—In this paper, an improved solution for drug distribution is presented. It is divided into two parts: i) a Multi-Operator Evolutionary Algorithm in charge of calculating the initial delivery routes and ii) an Ambient Intelligence based support system able to tracing the merchandise along the distribution route. The first one establishes the routes to be followed by the vehicles, based on an estimation of the travel time taking into consideration the different cities in which the clients are located and the time of day at which a road is traversed. The second one is formed by a system able to recognize and trace the drugs inside each vehicle in real time and to detect whether a package is not delivered to its expected destination.**

To demonstrate the adequacy of the system, laboratory experimentation has been conducted in order to validate the route calculator in the worse cases to be faced by the distributor. In addition, field experimentation has been carried out by implementing the traceability system in a delivery van which was the property of the drug distributor.

***Index Terms*—Intelligent Transportation Systems; Mobile information systems; Traceability; Radio Frequency Identification (RFID); Supply Chain Management; Combinatorial Optimization; Genetic Algorithms**

I. INTRODUCTION

Drug distribution presents particular challenges. Due to the intense competition between distributors, they are forced to maintain a high quality of service, without increasing costs. Since it is a market where most competitors offer similar products and prices, service quality is a key factor, so significant delays or wrong deliveries can end in the loss of a client [1]. These requirements are the responsibility of the warehouse employees who have to schedule deliveries and routes, and the carrier who is expected to complete the route without making mistakes in deliveries.

A traceability system in the supply chain can be described as *the documented identification of the operations which leads to the production and sale of a product* [2]. Thus traceability refers to the capability of tracing goods. The opportunity to connect traceability with the whole documentation and control system is an effective means of boosting the consumer's perception of quality [3].

From the perspectives of economics and health, the pharmaceutical drug supply chain must be controlled at all of its stages: from the production phases in the laboratory until the products reach the pharmacies where they are sold to the public. These requirements are reflected by the Spanish Ministry of Health and Consumption through the new Royal Decree on drug traceability, developed in accordance with Directive 2003/94/EC of the European Commission [4]. Moreover, the added costs are hardly permissible in an industry where profit margins use to be set by administrations [5].

Due to the quality requirements demanded, it is essential to deploy a holistic system that meets the new regulations, a high quality of service, and does not complicate the current tasks of the carriers [6] e.g., the installation of a system that needs the use of hardware, such as handheld Radio Frequency Identification (RFID) [7], [8] readers or similar devices, cannot be considered a solution because they add new tasks to an inherently stressful job.

Numerous studies have been focused on monitoring the drugs distribution during the last decades [9]–[11]. More recently, in [12], both the technical and business related adaptations involved in the transformation toward a RFID-aided drugs supply chain are analyzed. [13] discusses about how RFID can be applied to increase the integrity and confidence in the pharmaceutical supply chain. [14] states that the lack of system-level design methodologies was one of the main obstacles to adopt WSNs or RFID systems in industries.

The contribution presented in this article is a system designed to adapt the a drug distributor to the new regulatory environment without altering the behavior of the workers involved in it. Besides, by using this system, the overall quality of service is enhanced. First, an in-house system based on evolutionary algorithms [15] for a better scheduling of the distribution routes is deployed. The algorithm integrates the adaptation of the crossover probability with the capability of selecting the crossover operator depending on the state of the execution. Second, an onboard system mounted in delivery vans collects data required for traceability without human interaction, by using an embedded RFID system [16]. Furthermore, this last system is responsible for real-time incident detection by invalidating all actions which vary the cargo during the development of a route. It notifies the carrier only if detects a deviation from the plan.

In order to test the proposal, a method to estimate travel times in the locations near to the city of Bilbao is presented, using its results to build a test set compounded of seven instances, that are tested under three different capacities of the distribution van. In the end, the result is an implementation of a smart environment combining in-house expert systems with wireless scenarios and with a flexible system architecture to support real-time monitoring and interaction [17]. Thus, it depicts a successful experience of using artificial intelligence algorithms in combination with ambient intelligence (AmI)

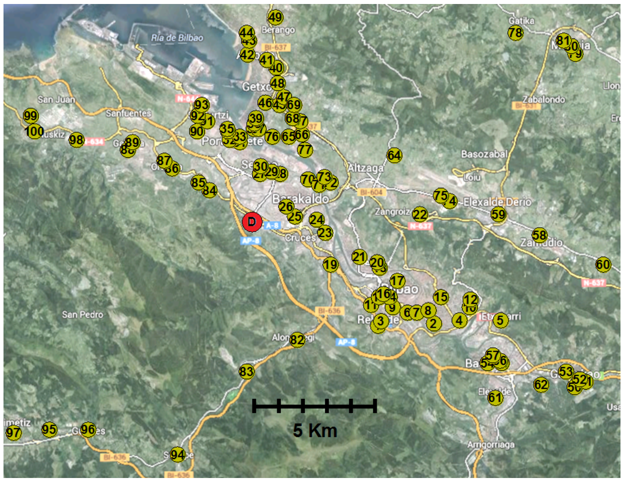

Fig. 1. An aerial view of Bilbao's surroundings, showing the distribution of the pharmacies

environments in order to resolve a real logistic problem [18].

This paper is organized as follows. Section II presents the mathematical model used to mimic the scenario faced by a distributor and proposes a meta-heuristic to optimize delivery routes. Section III describes an AmI environment, based on an intelligent van. The experiments carried out in order to demonstrate the usefulness of the implemented routing meta-heuristic is presented in Section IV. A validation of the developed identification and traceability system once implanted in a real warehouse is presented in Section V. Finally, Section VI makes some concluding remarks and outlines possible future research.

II. Proposed routing problem and solver

Route scheduling is an important process in developing applications in the field of logistics. For most environments, the travel time is the most relevant criterion when planning a route. This section proposes a specific variant of the Vehicle Routing Problem (VRP) in which travel times along stations are calculated considering the cities in which they are located, and the time of day at which the route is scheduled. In addition, a scheduler based on evolutionary algorithms with multiple crossover operator and adaptive crossover probabilities is designed to plan the route to be followed by the fleet of vans.

A. Description of the problem

Considering the problem of a drug distribution company, a test set consisting of 100 pharmacies and a depot has been developed. The locations selected pharmacies in the surroundings of the city of Bilbao are represented by their latitude and longitude, taken from $http://maps.google.com$. The pharmacies are distributed in 31 different cities. Figure 1 shows the distribution of the pharmacies, and the depot is marked with a D.

All the vehicles are supposed to have the same capacity, which is varied in the experimentation (Section IV-A). The vehicles are supposed to initiate their routes at 8:00 am. To better fit the real world, travel times between two given pharmacies i and j are calculated in two ways: $t^r_{(i,j)}$, which denotes the travel time during rush hours (between 8:00 am and 10:00 am and between 1:00 pm and 3:00 pm), while $t^n_{(i,j)}$ indicates the travel time during the rest of the day. This distinction is made since it is assumed that it is much more costly to travel between two points at rush hours, where traffic congestion is much higher than at other times of the day.

Each pharmacy has an associated service time, which also varies depending on the hour at which is visited by the vehicle. In this case, it is assumed that the rush hour is when there is a greater influx of people into the city. s^r_i depicts the service time of pharmacy i in influx rush hour, which is between 10:00 am and 12:00 pm. The rest of the day, time service is represented by s^n_i. In this way, the following aspects are established for each pharmacy i:

$$\begin{aligned}
Demand_i &= 1 && ,\forall i \in \{1,3,5,7,...,99\}\\
Demand_i &= 2 && ,\forall i \in \{2,4,6,8,...,100\}\\
\{s^n_i = 300s,\ s^r_i &= 500s\} && ,\forall i \in \{1,2,5,6,...,97,98\}\\
\{s^n_i = 600s,\ s^r_i &= 800s\} && ,\forall i \in \{3,4,7,8,...,99,100\}
\end{aligned}$$

$Demand$ represents the number of containers needed for transporting the delivery to the pharmacy. In Figure 9, the reusable containers used to transport the orders can be noticed.

In addition, for a greater adaptability to the real world, the problem presented in this paper considers a dynamic situation. This dynamism will cause route replanning. This feature is detailed in Section II-A2. Before that, Section II-A1 explains the calculation of the travel times between pharmacies.

1) Travel time calculation: Pharmacies are clustered according to the cities in which they are located. In addition, there is defined a circular *frontier*, with center calculated as the average position of the pharmacies in the city and radius calculated as the longest distance from the center to a pharmacy in the city plus a threshold (in this case of 200 m).

In order to calculate travel times between pharmacies, it is assumed that the Euclidean distance $d(i,j)$ between two pharmacies can be traveled at six different speeds:

$$\begin{aligned}
V^{n|r}_{closer} &= && \{35,25\}km/h\\
V^{n|r}_{away} &= && \{40,30\}km/h\\
V^{n|r}_{highway} &= && \{75,50\}km/h
\end{aligned}$$

where the subscripts $closer$ and $away$ denote the speed used to approach/leave the center of the city, $highway$ represents the speed used in travels between cities. The superscript n and r denote that the trip is done during normal/rush hours. To define the speeds, it has been assumed that: i) at rush hours, speeds must be lower; ii) to get closer to the city center is slower than to leave the city, and iii) to move between cities is faster than to move inside the city. In addition, the time to move between two pharmacies i and j is calculated in three different ways, depending on their locations.

If both pharmacies are in the same city, and assuming pharmacy i is nearer to the city center than pharmacy j, travel times are calculated as shown in Equations (1) and (2).

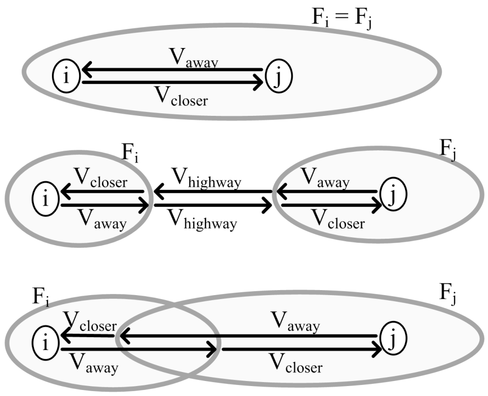

Fig. 2. Graphical example of speeds used to cover the distance between two pharmacies: in the same city (top), in different cities (center), in different and overlapping cities.

$$t^{n|r}_{(i,j)} = d(i,j)/V^{n|r}_{away} \quad (1)$$
$$t^{n|r}_{(j,i)} = d(j,i)/V^{n|r}_{closer} \quad (2)$$

If both pharmacies are in different cities, the line that joins them is divided into three pieces with lengths $d(i, F_i)$, $d(F_i, F_j)$, and $d(j, F_j)$, the first denoting the distance between the pharmacy i and the frontier F_i of its city, the second, the distance between the two relevant frontiers F_i and F_j, and the third, the distance between the pharmacy j and F_j. With this, travel times between any two pharmacies in different cities are calculated, as presented in Equations (3) and (4).

$$t^{n|r}_{(i,j)} = \frac{d(i,F_i)}{V^{n|r}_{away}} + \frac{d(F_i,F_j)}{V^{n|r}_{highway}} + \frac{d(j,F_j)}{V^{n|r}_{closer}} \quad (3)$$
$$t^{n|r}_{(j,i)} = \frac{d(j,F_j)}{V^{n|r}_{away}} + \frac{d(F_i,F_j)}{V^{n|r}_{highway}} + \frac{d(i,F_i)}{V^{n|r}_{closer}} \quad (4)$$

The third case is where the pharmacies are in different cities, but they overlap. Then, the arc is divided into two pieces with lengths $d(i, F_i)$ and $d(F_i, j)$. The travel times are calculated as in Equations (5) and (6).

$$t^{n|r}_{(i,j)} = \frac{d(i,F_i)}{V^{n|r}_{away}} + \frac{d(F_i,j)}{V^{n|r}_{closer}} \quad (5)$$
$$t^{n|r}_{(j,i)} = \frac{d(j,F_j)}{V^{n|r}_{away}} + \frac{d(F_j,i)}{V^{n|r}_{closer}} \quad (6)$$

Figure 2 represents graphically the situations considered to calculate the travel time. It is important to note that the speeds used in Equations. (1) to (6) are different depending on whether they are calculated for normal or rush (superscript n or r) hours.

2) Incidence Management: Bringing dynamism to routing problems is a relatively new practice which many researchers have emphasized in recent years [19]. Dynamism makes it necessary to modify or reschedule the pre-planned routes, either because of an incident or the arrival of new information that was not present at the beginning of the scheduling. The significance of dynamism is highlighted by the wide variety of environments in which it can be applied, and it can be modeled in many different ways.

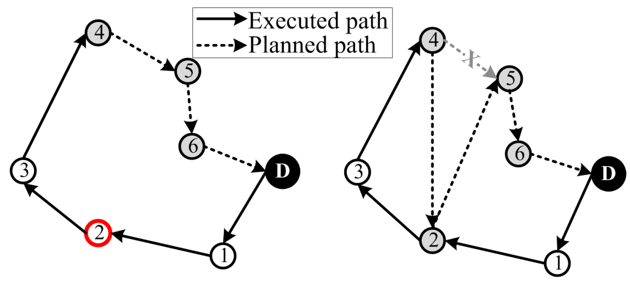

Fig. 3. Example of high priority incident treatment.

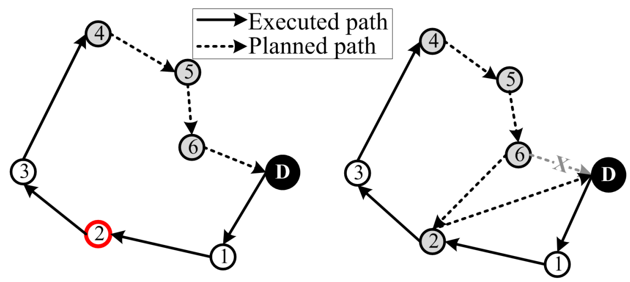

Fig. 4. Example of low priority incident treatment.

In the present case, the dynamism introduced by an incident occurs in case a delivery for a pharmacy has suffered a problem, e.g., an incomplete delivery. In such a case, the system has to react to this incident, and the affected route has to be rescheduled, in order to complete the service. It is assumed that pharmacies must be revisited by the same vehicle that made the first delivery, since this vehicle is the only one that has the products needed to complete the initial order.

The re-planning of the route is made as a function of a parameter of priority $Prio_i$, which is assigned to each pharmacy i. $Prio_i$ can take two values: high priority (H) and low priority (L).

In the first scenario, at the time the notification of Inc^t_i is received, the route has to be modified, giving priority to supply i. A visual example of this case is shown in Figure 3, where the initial planned route $\{1, 2, 3, 4, 5, 6\}$ is shown. At the time when the vehicle is on the way between the clients 3 and 4, a notification Inc^t_2 arrives. Assuming that $Prio_2 = H$, the system reacts by giving priority to supplying 2. Thus, the remainder of the route, $\{4, 5, 6\}$, is modified to $\{4, 2, 5, 6\}$.

On the other hand, if i has $Prio_i = L$, the route is modified by reinserting i in a place that involves a smaller increase in the cost of the route. An example of this is presented in Figure 4, where the situation is the same, the notification Inc^t_2 arrives when the vehicle is on the way between the clients 3 and 4. In this case, it is supposed that $Prio_2 = L$, and the remainder of the route, $\{4, 5, 6\}$, is modified to $\{4, 5, 6, 2\}$.

Finally, in the presented problem, $Prio_i$ is established as follows:

$$Prio_i = L, \forall i \in \{[1 \to 4], [9 \to 12], ..., [93 \to 96]\}$$
$$Prio_i = H, \forall i \in \{[5 \to 8], [13 \to 16], ..., [97 \to 100]\}$$

Furthermore, the incident Inc_i^t has two parameters, i, which is the affected pharmacy, and t, which represents the time (in seconds) that elapses between the vehicle's arrival at i and the arrival of the notification.

3) Summary: With all the considerations made in the previous sections, it is important to note that, in this paper, a rich model of the classical VRP has been considered. It includes the following aspects:

- Variable travel times: The travel time between two pharmacies is different in rush and normal hours. This increase the complexity of the problem, bringing originality to the problem, and few are the occasions at which is has been previously treated [20].
- Variable service times: Pharmacies have two different service times assigned, depending again on the time of the day. As in the above feature, this gives originality and complexity to the model.
- Asymmetry: Unlike most routing problems treated in the literature, the costs are asymmetric. This feature adds complexity and realism to the problem, and it has been used previously in the literature [21].
- Dynamism: As explained in Section II-A2, the model provides dynamism to the problem.

With all this, in this paper a variant of the VRP called Dynamic Asymmetric Capacitated Vehicle Routing Problem with Variable Service and Travel Times (DAC-VRP-VSTT) is presented and tested. The objective of the problem is to find a set of routes which minimizes the total time needed and satisfies the following conditions: i) all the pharmacies have to be visited once and only once (dynamism apart), ii) all the routes have to start and finish at the depot, iii) the vehicle capacity must be respected, and iv) all incidents must be resolved. In a formal way, the objective function (to be minimized) is presented in Equation 7.

$$\sum_{j \in N} x_{ij}^n t_{ij}^n + x_{ij}^r t_{ij}^r + \sum_{j \in N} y_i^n s_i^n + y_i^r s_i^r \tag{7}$$

where $t_{ij}^{n|r}$ and $s_i^{n|r}$ denote the travel and service time in normal or rush hours, and $x_{ij}^{n|r}$ and $y_i^{n|r}$ are binary variables denoting if a certain arc/node is used in the solution.

B. Proposed technique for the DAC-VRP-VSTT

Taking into consideration that the algorithm is applied to a real environment for the distribution of goods to pharmacies, it was opted for a technique which would be simple to implement and quick to execute. The meta-heuristic used is an Adaptive Multi-Crossover Evolutionary Algorithm (AMCEA). This algorithm was first introduced in [22], and has proven to be a competitive alternative to solve routing problems, such as the Traveling Salesman Problem [23], the Capacitated Vehicle Routing problem [24], and Vehicle Routing with Backhauls [25].

```
P ← Initialize the population
repeat
    Evaluate(P)
    P_M ← Mutation(P,p_m)
    Evaluate(P_M)
    P_C ← Crossover(Selection(P),p_c)
    Evaluate(P_C)
    P ← SurvivorSelection(P ∪ P_M ∪ P_C)
    if Best solution found has been improved then
        Restart p_c
    else
        if maxp_c reached then
            Change the crossover function
            Restart p_c
        else
            Increase p_c
        end
    end
until termination criterion reached;
Return the best individual found
```

Algorithm 1: Pseudocode of the proposed AMCEA

The proposed AMCEA is a variant of the classic Genetic Algorithm (GA) [26]. Algorithm 1 presents its pseudo-code. Its main characteristics are as follows:

- AMCEA reverses the philosophy of conventional GAs. It starts with a very low or null value for the crossover probability p_c and a high value for the mutation probability p_m.
- Instead of relying on the population fitness, as most previous studies [27], [28], the proposed technique adapts p_c depending on the current generation number and the search performance in recent iterations.
- The proposed algorithm combines the p_c adaptation and the multi-crossover mechanism.

Regarding the adaptive mechanism, in each generation, p_c of the algorithm is modified depending on the result obtained in the previous generations. If the best solution found by the technique has been improved in the last generation, p_c is restarted from 0. Otherwise, p_c increases based on the following Equation (8).

$$p_c = p_c + \frac{2 \cdot G_{wi} + G}{N_I^3} \tag{8}$$

where G_{wi} is the number of generations executed without improvements, G is the total number of generations executed, and N_I is the number of individuals in the population.

As to the multi-crossover feature, the proposed AMCEA uses more than one crossover operator, which are alternated during the execution. At the beginning, one operator is assigned at random. Along the execution, the operator is randomly replaced by another available when necessary, allowing repetitions. For this purpose, a maximum p_c value is defined: $maxp_c$. If over the generations p_c exceeds $maxp_c$, the crossover function is replaced at random by another one, and p_c is restarted with the initial value.

1) Encoding and operators: For the proposed DAC-VRP-VSTT, individuals have been encoded using an adaptation of the path representation [29]. In this case, the routes are also represented as a permutation of nodes. To distinguish the routes of one solution, they are separated by zeros. For example, a solution with three routes, for instance $\{2, 5, 7\}$, $\{1, 8, 6\}$ and $\{4, 3, 9\}$, is encoded as: {**0**, 2, 5, 7, **0**, 1, 8, 6, **0**, 4, 3, 9, **0**}. This encoding has been previously used in the literature for the VRP and its variants [30].

The crossover functions used for the proposed AMCEA are the Short Routes (SR), the Random Routes (RR), and the Large Routes (LR) crossovers. With the SR, first, the shortest 50% of the routes in one randomly chosen parent are selected and inserted in the child. Then, the nodes already inserted are removed from the other parent. Finally, the remaining nodes are inserted in the same order in the final solution, creating new routes. The RR works similarly to the SR. In this case, in the first step, the routes selected from one of the parents are chosen randomly, instead of selecting the shortest ones. Ultimately, in LR, the longest 50% of the routes of one randomly selected parent are selected. Then, as in SR and RR, the remaining nodes are inserted in the same order that they appear in the other parent.

The mutation function used is an adaption of the classic insertion mutation [31], which is called Vertex Insertion Routes. This function selects and extracts one random node from a random route. Then, the node is inserted at a random position in another randomly selected route. New route creation is possible with this function.

Finally, in the developed AMCEA, a binary tournament selection has been used to select parents to be crossed. In addition, a half elitist – half random function (without repetitions) has been developed as the survivor function. First, the best 50% of the individuals of the whole population is selected for the next generation. The remaining individuals are randomly selected among the ones generated in the mutation and crossover phase.

III. Proposed Intelligent Van for Real Time Incident Reporting

One of the critical characteristic of the proposed system is the possibility of allowing incident reporting in real time. In order to achieve this goal, this section presents the incorporation of RFID technology in pharmaceutical drug distribution. Section III-A justifies the use of the RFID technology, and presents the overall working of the system, and subsequently Section III-B gives the details of the characteristics of the ambient intelligence system implemented.

A. The adoption of RFID technology in the drug distribution scenario

Once the destination of each container is known, dispense robots organize all requested products in containers ready to be loaded into distribution vans. Passive transponders are attached to containers so their electronic product code (EPC) is related to drugs inside each container and its destination.

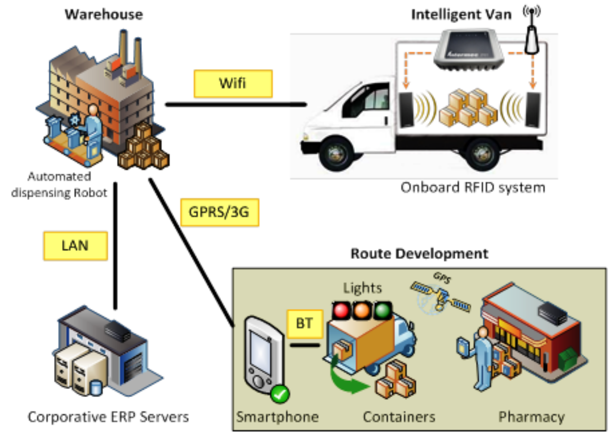

Fig. 5. Agents and interaction in the drug distribution chain.

Figure 5 shows the interactions between the main agents in the distribution chain. When the delivery van arrives at the warehouse, its onboard system is connected to the office via Wi-Fi in order to download the needed information about the route to take, calculated as presented in Section II-B.

Once vans start being loaded, an RFID reader module located inside the van detects each container that enters or leaves the van. The RFID module detects the transponders' EPCs and sends them to the onboard system. In case of a mistake loading or unloading a container, a red light is switched on in the trunk, indicating that there is a problem.

Since all drivers carry a smartphone, an application (Section III-B3) informs the them via Bluetooth. The driver can try to solve the mistake. If this is not possible, the application sends a report to the manager. In addition, in case the route needs to be modified, the method proposed in Section II-A2 is applied. If the process is done as planned, the driver does not need to use the application, thus simplifying its use.

Once the cargo is loaded, the driver starts the route. By means of global position system (GPS), the van knows its location. When the van stops and its door is opened, the system detects the nearest pharmacy in the route. It checks for the unloaded containers and switches on a green light when all the desired containers have left the van (i.e., it senses that the corresponding RFID tags are not present). In case the green light remains off, the carrier have to use the mobile application to check the cause of the problem. If there is any unsolvable problem, the carrier can continue the route, and the system reports an incident to the manager.

It is important to note that this is a non-intrusive system, and the carrier does not have the need of registering loads or unloads. In this way, the carrier can work in the usual way, not realizing that the system monitors each event and notifies the warehouse only in case of an error.

The system also stores the location of the van and EPCs of containers loaded at regular intervals. Once the van returns to the warehouse, the system sends an XML file through File Transfer Protocol (FTP) containing the information stored during the route.

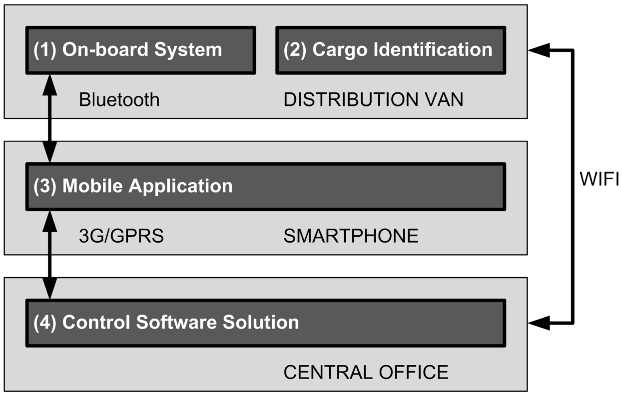

Fig. 6. Description of the system architecture and communications.

B. Implementation of the ambient intelligence system

The core of the environment is given by the intelligent van in which an onboard system is installed. A specific middleware for communication has been developed to connect the system with the rest of the modules that compose the system architecture.

Figure 6 shows the implemented architecture, which can be decomposed into four different parts: i) the onboard system itself; ii) the cargo identification system; iii) the mobile application; and iv) the control software solution. Next, each module is described from a functional and technical point of view, for a more detailed description, refer to [16].

1) Onboard system: The system is implemented in an ISEE IGEPv2 MPU platform based on a DM3730, this is a system on a chip that integrates a 1 GHz ARM Cortex-A8 Core. This is a small sized card (93 × 65 × 15 mm) containing the communication resources demanded by the project. The platform runs under a Linaro distribution including Wi-Fi communication for updating information at the warehouse and Bluetooth for communicating with the mobile application. The platform has global purpose input/ouput pins, used to activate the lights and to detect when the van doors are opened.

Furthermore, the board has serial ports, that are used for communication with the RFID reader and the GPS receiver. Finally, the platform has an SD card to store data acquired. The onboard system is powered by an independent battery, charged from the supply system of the van.

2) Cargo identification system: The system is able of determining the place where the containers have been left, supported by the GPS. The attachment of a passive tag to containers makes the investment affordable, while allows the system to know containers that enter or leave the van.

With respect to the RFID tags, Confidex's Carrier Tough (Figure 9) tag was chosen to be attached to containers. Tags work using EPC Gen2 Class1 protocol, with frequency 860–960 MHz, and its reading range is 4–6 m (enough for a van).

The RFID reader located in each van has RS-232 communication with the embedded device and wireless communication with the passive transponders. A ThingMagic's Mercury5e-EU RFID Reader has been used [32], operating at the UHF frequency range to improve the interrogation distance, and bears the EPC Gen2 protocol, which is more robust against

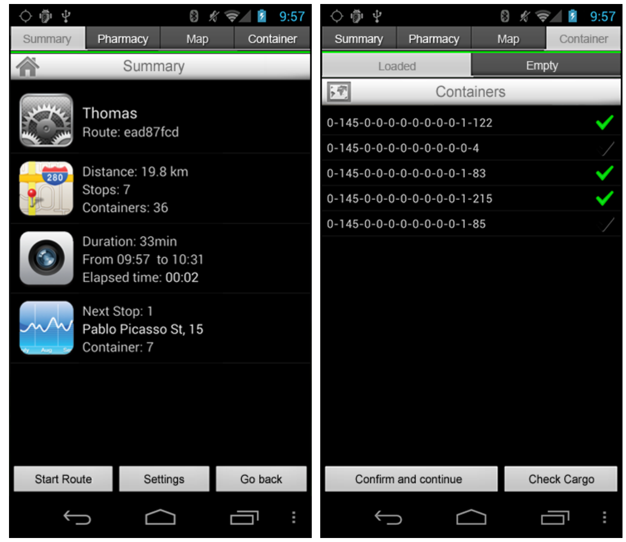

Fig. 7. Screenshots of the developed mobile application. Delivery's summary (left) and loaded containers (right).

noise and interferences. It has 30 dB read gain within the range of 865.6–867.6 MHz. With an antenna of at least 6 dBi, it can read tags at 9 m within its nominal sensitivity of -65 dBm.

3) Mobile application: The use of a mobile device in the solution supports the driver with information offered in a more direct manner [33], maintaining the level of non-intrusiveness [34]. In this way, a multiplatform application that works on most of the existing smartphones (Android, Apple, BlackBerry) has been implemented.

Figure 7 shows the interface of the implemented mobile application. The application supports: i) management of incidents and report of them to the control center, ii) navigation aid to the driver and iii) detection of changes in the cargo by reading the RFID tags.

4) Control software solution: It relates to an application for monitoring drug traceability, schedule optimized routes, and locate vehicles of the fleet. The developed control panel includes: i) product traceability, ii) fleet management and iii) optimized schedules (Section II).

The control panel is based on the ASP.NET development framework and has been implemented making use of JavaScript, CSS3, HTML5, Ajax and jQuery, using also tools offered by *Google* for displaying geographical information (Figure 8).

IV. Experimentation with the Routing Algorithm

This section describes the conducted experimentation with the routing process, which consists in applying the designed AMCEA (Section II-B) to the proposed DAC-VRP-VSTT (Section II-A). The procedure to generate instances used in this experimentation is detailed in Section IV-A, in order to increase its reproducibility. This section finalizes by presenting the obtained results (Section IV-B).

A. Details of the experimentation

In the experimentation, the outcomes obtained by the proposed AMCEA have been compared with the ones obtained

Fig. 8. Web interface of the software solution.

by three different classical GAs. Each GA has the same parameters, and the only difference between them is the crossover function employed. An initial population of $N_I = 75$ randomly generated individuals is used for all the algorithms. The p_c of every GA is 100%, and the p_m has been set at 10%. For the AMCEA, the p_m has been established in 100%, which means that the mutation is applied to all individuals each generation. The initial p_c has been set at 0%. Along the execution, this p_c evolves in accordance with Equation (8). In addition, $maxp_c$ has been established at 50%. Finally, the execution of every technique finishes when there are $n/2 + \sum_{k=1}^{n/2} k$ generations without improvements in the best solution, where n is the size of the problem (number of nodes).

As reproductive operators, functions explained in Section II-B1 have been used for the different GAs. All of them use the insertion function as mutation function. In this way, the three GAs are defined as GA_{SR}, GA_{RR} and GA_{LR}, depending on the crossover function used.

In order to carry out a proper experimentation, apart from using the instance presented in Section II-A, with 100 pharmacies ($Pharmacies100$ from now), another six instances have been generated using subsets of 50 and 75 pharmacies:

$$Pharmacies75A = Pharmacies100 - \{1, 5, 9, \ldots\}$$
$$Pharmacies75B = Pharmacies100 - \{2, 6, 10, \ldots\}$$
$$Pharmacies75C = Pharmacies100 - \{3, 7, 11, \ldots\}$$
$$Pharmacies75D = Pharmacies100 - \{4, 8, 12, \ldots\}$$
$$Pharmacies50A = Pharmacies100 - \{1, 3, 5, \ldots\}$$
$$Pharmacies50B = Pharmacies100 - \{2, 4, 6, \ldots\}$$

Each instance has been executed assuming three different capacities for the vehicles ($Q = \{10, 20, 30\}$), measured in the number of containers that they can transport.

B. Results

The tests have been performed on an Intel Core i5 2410 laptop, with 2.30 GHz and a 4 GB of RAM. JAVA was used as the programming language. Each experiment was repeated 30 times. The outcomes are shown in Table I. For each run, the total, average, and standard deviation are displayed, as well as the computational time (in seconds). The best result found for each instance is displayed in Table II. It is noteworthy that the AMCEA is the technique which has obtained the best averaged results in all the cases.

TABLE II
BEST SOLUTION FOUND FOR EACH INSTANCE, AND NUMBER OF VEHICLES USED. ALL THE SOLUTIONS HAVE BEEN OBTAINED BY AMCEA

Instance	Q	Best Solution Found	N_V
Pharmacies50A	10	28900.93	8
	20	25507.86	4
	30	24689.29	3
Pharmacies50B	10	43076.89	8
	20	39926.54	4
	30	38967.98	3
Pharmacies75A	10	56476.27	13
	20	51183.94	7
	30	49377.49	5
Pharmacies75B	10	54207.02	10
	20	50058.70	6
	30	48390.30	4
Pharmacies75C	10	49968.68	13
	20	43955.45	7
	30	42215.40	5
Pharmacies75D	10	47114.97	11
	20	42954.08	6
	30	41774.38	4
Pharmacies100	10	67677.87	16
	20	61269.73	8
	30	59156.44	5

Two statistical tests have been performed according to these results. The first one is the normal distribution z-test. By this test, the results obtained by the proposed AMCEA are compared with those obtained by the other techniques. Using the normal distribution z-test, it can be concluded whether the differences in the outcomes are statistically significant or not. The z statistic has the following form:

$$z = \frac{\overline{X_{AMCEA}} - \overline{X_{other}}}{\sqrt{\frac{\sigma^2_{AMCEA}}{R_{AMCEA}} + \frac{\sigma^2_{other}}{R_{other}}}} \tag{9}$$

where $\overline{X}$, σ and R represent the averaged results, standard deviation and number of repetitions for a technique.

The confidence interval has been stated at 95% ($z_{0.05} = 1.96$). Thereby, AMCEA's results are significantly better that the ones obtained by other techniques if $z \geq 1.96$. Table III displays the z values obtained when comparing AMCEA with the three versions of the GA implemented. In the table, it can be seen that, for all the cases AMCEA outperforms the rest of the techniques.

The second statistical test performed is Friedman's test [35]. In Table IV, the results of overall ranking calculated using this test are summarized, where the smaller the score, the better the ranking. This ranking is conducted considering the average results of each technique, and comparing them instance by instance.

Furthermore, in order to check if there are statistical differences between the developed techniques, the value of X_r^2 is also depicted in Table IV. This value has been obtained using the following formula:

TABLE I

RESULTS OF $AMCEA$, GA_{SR}, GA_{RR}, AND GA_{LR} FOR THE DAC-VRP-VSTT. FOR EACH INSTANCE, THE AVERAGE RESULTS, THE STANDARD DEVIATION, AND THE TIME AVERAGE ARE SHOWN.

		AMCEA			GA_{SR}			GA_{RR}			GA_{LR}		
Instance	Q	Avg.	S. dev.	time	Avg.	S. dev.	time	Avg.	S. dev.	time	Avg.	S. dev.	time
Pharmacies50A	10	**29348.2**	298.2	8.5	30524.6	688.2	12.1	30304.4	458.7	12.2	30999.3	1066.4	12.4
	20	**26280.5**	400.4	8.4	27005.9	549.6	13.5	27322.0	731.7	13.3	27673.8	751.0	13.4
	30	**25204.9**	327.9	9.8	26842.5	773.0	12.1	27160.3	839.5	11.8	26094.7	524.7	12.2
Pharmacies50B	10	**44085.7**	544.6	7.1	44971.0	716.5	10.9	44796.4	681.1	10.8	45783.4	959.2	10.9
	20	**40870.0**	471.1	6.7	41738.4	586.5	10.4	41895.7	548.9	10.7	42002.3	807.5	11.1
	30	**39908.6**	438.0	9.5	41435.7	831.0	10.8	41492.4	576.0	10.8	41325.6	742.4	11.0
Pharmacies75A	10	**57507.0**	618.7	16.8	61233.8	1799.7	21.3	61175.4	1703.7	21.5	61787.1	1529.5	21.3
	20	**51921.7**	529.6	19.3	54641.6	1383.1	27.5	55293.2	1367.6	27.8	58069.9	2273.2	28.0
	30	**50667.4**	688.3	19.1	53214.3	1239.5	23.7	54693.7	1961.9	23.4	54574.5	1251.0	23.3
Pharmacies75B	10	**55162.0**	690.5	14.8	58348.4	1767.5	21.7	58293.4	2158.5	21.5	61080.7	1995.8	21.9
	20	**51368.3**	770.7	15.2	53973.0	1156.7	21.0	55341.5	2120.8	21.2	56145.4	2307.9	21.4
	30	**49488.2**	803.9	16.5	52286.9	1153.1	20.6	52508.1	1524.0	20.4	54595.1	1328.0	20.7
Pharmacies75C	10	**50754.6**	492.5	16.1	53657.5	1520.1	21.4	53541.4	1211.3	21.5	53256.3	1590.0	21.7
	20	**45065.9**	627.2	20.7	48353.1	1244.9	20.2	47844.2	1354.2	20.0	49932.1	1744.6	19.9
	30	**43423.9**	665.2	15.3	46627.2	1225.2	22.3	47531.1	1518.4	22.4	48221.3	1535.5	22.8
Pharmacies75D	10	**48300.3**	628.7	14.0	52374.1	1425.1	20.8	52217.5	1748.2	21.1	54503.3	1578.5	20.7
	20	**44480.4**	1116.8	16.4	47981.8	2039.3	22.1	47399.2	1781.9	21.7	49857.4	1551.9	21.9
	30	**42625.5**	550.6	18.5	45106.6	1118.3	23.0	45482.8	1896.0	22.8	47566.0	1442.0	23.2
Pharmacies100	10	**69467.6**	818.8	30.1	75020.7	1751.8	42.3	75316.5	2396.7	42.7	76354.0	3955.8	43.1
	20	**62263.3**	667.0	34.0	67934.8	4692.8	42.1	66227.3	2450.4	41.9	68005.1	3431.6	41.8
	30	**60589.3**	1351.7	37.5	65996.5	2109.4	42.8	66767.5	2840.7	43.0	67591.4	3755.7	43.3

TABLE III

RESULTS FOR THE NORMAL DISTRIBUTION z-TEST.

Instance	Q	vs. GA_{SR}	vs. GA_{RR}	vs. GA_{LR}
Pharmacies50A	10	8.59	9.57	8.16
	20	5.84	6.83	8.96
	30	10.68	11.88	7.87
Pharmacies50B	10	5.38	4.46	8.43
	20	6.32	7.76	6.63
	30	8.90	11.98	9.00
Pharmacies75A	10	10.72	11.08	14.20
	20	10.06	12.59	14.42
	30	9.83	10.60	14.98
Pharmacies75B	10	9.19	7.56	15.35
	20	10.26	9.64	10.75
	30	10.90	9.59	18.01
Pharmacies75C	10	9.95	11.67	8.23
	20	12.91	10.19	14.37
	30	12.58	13.57	15.70
Pharmacies75D	10	14.32	11.54	19.99
	20	8.24	7.60	15.40
	30	10.90	7.92	17.53
Pharmacies100	10	15.72	12.64	9.33
	20	6.55	8.54	8.99
	30	11.82	10.75	9.60

TABLE IV

RESULTS OF FRIEDMAN'S TEST (SMALLER IS BETTER). THE LAST COLUMN DEPICTS THE X_r^2 VALUE.

Function	$AMCEA$	GA_{SR}	GA_{RR}	GA_{LR}	X_r^2
DAC-VRP-VSTT	**1.00**	2.57	2.76	3.66	45.52

$$X_r^2 = \frac{12}{H \cdot K \cdot (K+1)} \sum (H \cdot Rc)^2 - 3 \cdot H \cdot (K+1) \tag{10}$$

Here, $H = 21$ is the number of problem instances, $K = 4$ is the number of techniques, and Rc is the value of the Friendman's test ranking score. The confidence interval has been stated at the 99% confidence level. The critical point in a χ^2 distribution with 3 degrees of freedom is 11.345. In this case, because of $X_r^2 > 11.345$, it can be concluded that there are significant differences between the developed techniques.

The results depicted from this experimentation lead to the conclusion that the proposed AMCEA outperforms the implemented GAs, both in terms of result quality and runtimes. Anyway, it cannot be assumed that they are the optimal solutions.

V. VALIDATION OF THE AMBIENT INTELLIGENCE SYSTEM

The solution was tested in a pharmaceutical warehouse owned by the company Cenfarte S.A. Figure 9 shows the system mounted inside the test van, and its different elements are marked.

The vehicle has routes to be followed up to three times a day. A route covers a distance of about 26.4 km and includes a maximum of 12 pharmacies. The tests were carried out for six days on which the route was run 14 times. The average route duration was 97 minutes. To minimize the impact of the tests on the warehouse, the evaluation was carried out in three phases, which are described next.

In the first stage, the positioning system was tested. The tests were developed during the first two days of validation with five iterations of the routes. Table V reflects part of the results obtained during this phase. In the table can be seen, for each route, the time spent by the driver to unload the desired containers, as well as the distance from the parking space used by the van to the location of the pharmacy. During routes 1 and 3, the responsible driver was told to stop for about ten minutes in a non-planned location in order to validate the reconnaissance of the nearest pharmacy, resulting in incidents being logged into the XML file. As a result of this test, given the geographical issues, (some pharmacies are located in pedestrian areas), the need for modifying the structure of the database was highlighted. A field indicating the maximum distance of each pharmacy from the closest parking space was included.

In a second stage, tests were focused on the system for identifying the containers loaded in the van. This test was conducted six times. Table VI shows one of the experiments

TABLE V
RESULTS OF THE POSITIONING SYSTEM VALIDATION.

		WH	Ph_1	Ph_2	**Unknown**	Ph_3	Ph_4	Ph_5	Ph_6	Ph_7	Ph_8	Ph_9	Ph_{10}	WH	Avg.
$Route_1$	In Route?	Yes	Yes	Yes		Yes	Yes			Yes	Yes	Yes		Yes	
	Stopped?	Yes	Yes	Yes	**-Yes-**	Yes	Yes			Yes	Yes	Yes		Yes	
	Stop time (s)	455	324	250	**-543-**	262	278			330	253	262		503	342
	Distance to Pharmacy (m)	0	18	15	**-402-**	19	17			21	32	16		0	54
$Route_2$	In Route?	Yes	Yes			Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	
	Stopped?	Yes	Yes			Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	
	Stop time	479	300			241	298	373	375		312	222	335	477	336
	Relative distance	0	16			13	19	25	31		12	20	28	0	16
$Route_3$	In Route?	Yes	Yes	Yes		Yes			Yes	Yes		Yes	Yes	Yes	
	Stopped?	Yes	Yes	Yes	**-Yes-**	Yes			Yes	Yes		Yes	Yes	Yes	
	Stop time	436	345	302	**-599-**	261			274	288		235	315	511	348
	Relative distance	0	24	29	**-301-**	20			13	15		12	17	0	43

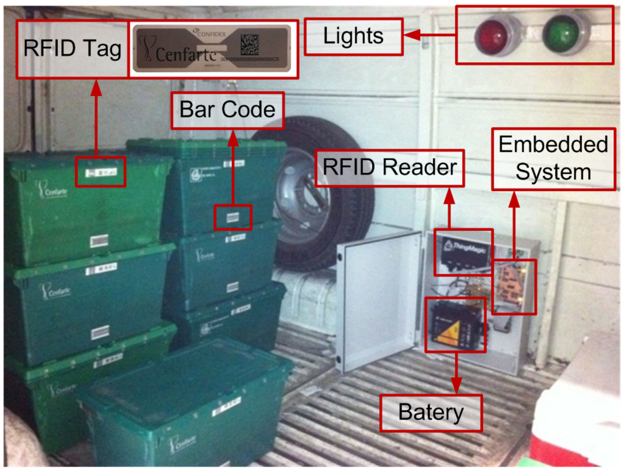

Fig. 9. Onboard system installed on the van. The containers (green boxes) and RFID tags can be seen at the left.

conducted. During the development of this test, 59 containers were transported to pharmacies in the route. Similarly, 52 empty containers were transported back to the warehouse. One container's destination, the third pharmacy, was mislabeled at the warehouse. It is important to note that the system detected the change and immediately informed the driver by switching on the red traffic light, and the corresponding incident was reported upon exiting the warehouse.

Finally, in the third phase, the complete system was tested in three routes (Table VII). In the first two routes, the driver was asked to be careful, in order to analyze incidence-free routes. In the 17 stops, the system confirmed the work carried out by the driver, switching on the green light. During the execution of the third route, the XML file containing the route information was manually altered by including three differences from the order given to the courier. Modifications included a container that was not loaded in the van (affecting delivery at the fourth pharmacy) and the switching of two pharmacies (the fifth and the seventh) of two containers. The three incidents were reported by SMS and email to the manager.

VI. CONCLUSION AND FUTURE RESEARCH

Nowadays, the quality of delivery systems has been improved gradually. Most of the existing solutions are aimed at the traceability of the products either in a manual o automatical way, but do not propose autonomously the tasks to be performed along the way from the receipt of the order. This could lead to a lack of accuracy in the information and in the generated incidents.

An adaptive multi-crossover evolutionary algorithm in charge of scheduling the routes to be followed by the vehicles has been designed. The proposal incorporates adaptation in the probability of crossover and dynamic selection of the crossover operator to use over the population. In addition, a method to recalculate routes in case of an incident is provided.

The solution proposed in the present paper is complemented with innovations that have not been included in most of the implemented traceability systems: such as the ability to perform cargo tracking and the monitoring of the distribution tasks interfere in the carrier's tasks.

The routing algorithm has been tested and compared with three versions of the classical genetic algorithm in a total of 21 instances of DAC-VRP-VSTT combining seven sets of clients and three capacities of the vehicles. The results show improved performances of the proposal in terms of quality of the solutions and execution times.

The overall ambient intelligence solution has been successfully implemented by a drug distributor of the city of Bilbao. During the integration of the system, its functionality was monitored and analyzed, in this way validating its adequacy.

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TABLE VI

RESULTS OF THE IDENTIFICATION SYSTEM VALIDATION.

		WH	Ph_1	Ph_2	Ph_3	Ph_4	Ph_5	Ph_6	Ph_7	Ph_8	Ph_9	Ph_{10}	WH	Avg.
$Route_1$	Door-open time	395	265	220	202	238			251	231	192		288	266
	Identified containers	**-16/17-**	4/4	3/3	**-2/3-**	4/4			6/6	5/5	4/4		15/15	**-59/61-**
	Cargo alteration	**-1-**	0	0	**-1-**	0			0	0	0		0	**-2-**
$Route_2$	Door-open time	395	265	220	202	238	320	266		231	192	266	408	266
	Identified containers	20/20	6/6	7/7	3/3	3/3	4/4	3/3		4/4	5/5	3/3	17/17	75/75
	Cargo alteration	0	0	0	0	0	0	0		0	0	0	0	0
$Route_3$	Door-open time	395	265	220	202	238	320	266	251		192	266	408	266
	Identified containers	23/23	5/5	5/5	3/3	3/3	3/3	5/5	10/10		3/3	4/4	20/20	84/84
	Cargo alteration	0	0	0	0	0	0	0	0		0	0	0	0

TABLE VII

RESULTS OF THE COMPREHENSIVE VALIDATION OF THE SYSTEM.

		WH	Ph_1	Ph_2	Ph_3	Ph_4	Ph_5	Ph_6	Ph_7	Ph_8	Ph_9	Ph_{10}	WH	Avg.
$Route_1$	Pharmacy assignment	OK	OK		OK	OK			OK	OK	OK		OK	OK
	Cargo identification	OK	OK		OK	OK			OK	OK	OK		OK	OK
	Incidences registered	0	0		0	0			0	0	0		0	0/0
$Route_2$	Pharmacy assignment	OK	OK	OK			OK	OK		OK	OK	OK	OK	OK
	Cargo identification	OK	OK	OK			OK	OK		OK	OK	OK	OK	OK
	Incidences registered	0	0	0			0	0		0	0	0	0	0/0
$Route_3$	Pharmacy assignment	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
	Cargo identification	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
	Incidences registered	**-1/1-**	0	0	0	**-1/1-**	**-2/2-**	0	**-2/2-**	0	0	0	0	**-6/6-**
Summary	Incidence reported to CO	**-Yes-**				**-Yes-**	**-Yes-**		**-Yes-**					
	Delay time in Inc. Report.	**-197-**				**-31-**	**-44-**		**-42-**					**-63-**

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