Routing optimization for ATM cash replenishment

Peter Kurdel, Jolana Sebestyénová

Abstract**—** The cash deployment strategy for a network of ATMs should take into account the analysis of inventory policies, logistics costs as well as the routing of replenishment vehicles. The optimal strategy has to focus on the reduction of cash-related expenses while safeguarding that ATMs do not run out of cash. Shorter routes with high time window constraints violations are not always the best solution. The problem, which can be tackled as a kind of rich vehicle routing problem is in the paper solved using parallel genetic algorithm. The proposed model is able to solve cases with simultaneous requirements of several replenishments for some of the customers (ATMs) several times daily as well as a single replenishment in several days for other groups of customers. Dynamic vehicle routing problem (VRP) must rely on up-to-date information. One type of dynamic model may consider new customer orders that arise after the routes had been initially planned. In the light of this information, the vehicles need to be re-routed so as to reduce costs and meet customer service time windows.

Keywords**—** ATM cash replenishment, genetic algorithm, multi-depot periodic vehicle routing problem, optimization, time window.

I. Introduction

Deriving the optimal cash deployment strategy for a network of ATMs involves the analysis of logistics costs, inventory policies as well as of the routing of replenishment vehicles. The problem is thus twofold, requiring first a conceptual framework to derive the optimal cash deployment strategy for a network of ATMs and second an assessment of potential benefits of sophisticated cash management software. Given the state of the ATM industry, the optimization objective is clearly to minimize costs.

Consequently, the optimal cash deployment and replenishing strategy focuses on the reduction of cash-related expenses providing at the same time that ATMs do not run out of cash. The study [1] develops a conceptual framework to derive the optimal cash deployment strategy for a network of ATMs and assesses potential benefits of sophisticated cash management software: logistics costs, inventory theory, routing (Travelling-salesman, Vehicle routing problem).

The Vehicle Routing Problem (VRP) is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or several depots must be minimized for a number of geographically dispersed cities or customers [2]. The VRP arises naturally as a central problem in the fields of transportation, distribution and logistics.

Combined VRP and Inventory Allocation Problem is Inventory Routing Problem (IRP). IRP objective is to minimize the overall inventory cost (holding and transportation) given that customers (e.g. ATMs) do not run out of stock at any given time. IRP has two sub-problems:

- Inventory allocation problem (determines the replenishment quantity and frequency)
- Routing problem (determines the delivery route).

Authors of [3] address a scheduling and routing problem faced by a third-party logistics provider in planning its day-of-week delivery schedule and routes for a set of existing and/or prospective customers that need to make shipments to their customers. The goal is to minimize the total cost of transportation and inventory while satisfying a customer service requirements that stipulate a minimum number of visits to each customer each week and fulfilment of time-varying demand at the end-customers.

Single-period models are well suited for instances with stochastic demand where forecasting [4] accuracy is low. If it is possible to predict clients requirements concerning amount of required goods (as it is in case of ATMs), usage of multi-period models with forecasting based on historical data is more advantageous.

The Periodic VRP (PVRP) is a multi-period vehicle routing problem in which the decisions are the service days for each customer and the vehicle routes for a service provider on each day. The emphasis is on minimizing routing costs and number of required vehicles.

In contrast to the PVRP, IRPs more strongly emphasize the trade-off between delivery and inventory-related costs. Logistics costs that need to be taken into account consist of: transportation costs (capacity, distance, …), holding costs (costs of banknote waiting one day, …), handling costs (packaging of banknotes in container), cost of capital (interest rate). The fixed vehicle cost includes vehicle depreciation, cost of capital, driver wages, order cost, insurance etc.

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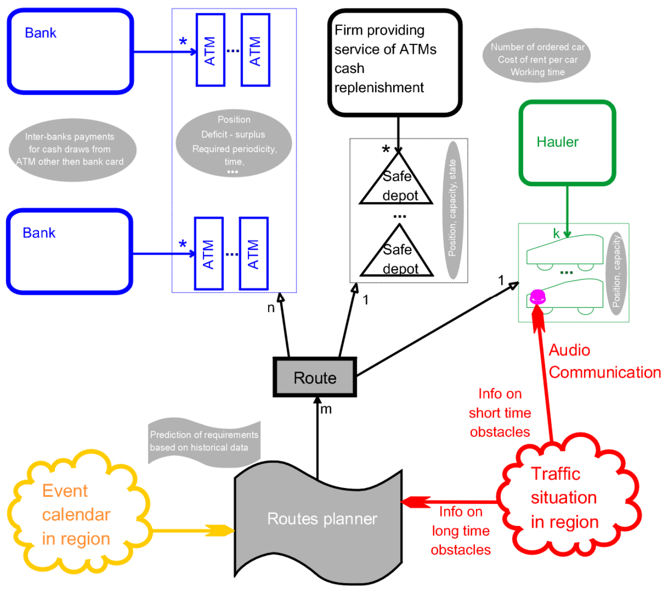

Fig. 1 Basic scenario

The basic scenario of this article will be the routing optimization for ATM cash replenishment. Similar solutions can be used for different applications, e.g. planning of tourist routes for bikes, waste gathering, etc.

Most often, a firm providing service of ATMs cash replenishment buys boxes containing banknotes from banks running ATMs. The firm owns one or more safe depots and each day it rents a certain number of cars from a shipping firm. Inputs to route optimizer (see Fig. 1) are: (1) Demands and time constraints of customers, i.e. required periodicity of the service for each ATM and time of the service based on cash withdrawals historical data. (2) Events calendar of a region; long term planned event can be used to modify typical requirements computed based on historical data. (3) Actual information on traffic situation can be used to re-route the travel ways in case of an accident; in other activities of the project, a possibility to direct communication with car drivers is worked out [5], [6].

Optimal strategy for ATMs cash replenishment is a multi-criterion problem, because there is more to optimize than just routes lengths. Services times need to be optimized in order to minimize diseconomy arising in case of too late and/or too early service. In the second case, bank notes boxes return to bank not being emptied, which creates loss for the firm providing the services, as it has already paid for the money.

Explicit constraints on the minimum number of visits to each customer during each time period give rise to interdependencies that result in a dimension of problem difficulty not commonly found in models in the literature. The proposed model combines a multi-periodic vehicle routing problem with assignment of time windows (TWs) to customers. The number of used vehicles is not constrained, but it should be as low as possible. It is supposed that each vehicle makes one route per day. Each route starts in one of the depots; while several routes can start in the same depot, there also can be a depot where no route starts. ATMs that require two visits per day are assigned TWs in 2 hours slots, the other ATMs are assigned wide TWs equal to a vehicles drivers working shift.

II. Solution Techniques for VRP

Optimization plays a central role in science and engineering. In optimization, the systems under consideration can often (but not always) be expressed in terms of a mathematical function, and the goal is then to find the minimum or maximum of this function. So, many problems can be formulated as the task of minimizing (or maximizing) a mathematical function, called the objective function. In most practical applications of optimization, there are constraints, i.e. limits on the allowed range of the variables. Unfortunately, classical optimization algorithms are not suitable for all optimization problems and one has to use alternative, stochastic algorithms, mostly inspired by biological phenomena.

Recent advances in evolutionary algorithms (EAs) focus on how to solve practical optimization problems. EAs are stochastic algorithms whose search strategies model the natural evolutionary phenomena. For the different types of optimization problems it is usually necessary to design a problem-oriented algorithm according to characteristics of the problem to be treated. Generally, EAs involve the following meta-heuristic optimization algorithms: genetic algorithm (GA), evolutionary programming (EP), evolution strategy (ES), genetic programming (GP), learning classifier systems (LCS), and swarm intelligence (comprising ant colony optimization ACO and particle swarm optimization PSO). Among them, genetic algorithms are the most widely known type of evolutionary algorithms today [7], [8].

The most commonly used techniques for solving Vehicle Routing Problems are modifications of Travelling Salesman Problem. Nearly all of them are heuristic and meta-heuristic because no exact algorithm can be guaranteed to find optimal routes within reasonable computing time when the number of cities is large. This is due to NP-hardness of the problem. The solution techniques can be classified as:

Exact Approaches: Every possible solution is computed until one of the best ones is reached (Branch and bound, Branch and cut).

Heuristics: Heuristic methods perform a relatively limited exploration of the search space and typically produce good quality solutions within modest computing times.

- Constructive Methods: They gradually build a feasible solution keeping in mind solution cost, but do not contain an improvement phase (savings, matching based, multi-route improvement heuristics)
- 2-Phase Algorithm: The problem is decomposed into its two natural components (Clustering of vertices into feasible routes, Actual route construction) with possible feedback loops between the two stages.

Meta-Heuristics: Meta-heuristics are applied to “*I know it when I see it*” problems [9]. These algorithms are used to find answers to problems when there is very little knowledge about the character of the optimal solution, very little heuristic information to build on and brute-force search is out of the question because the solution space is too large. But if there is a candidate solution to the problem, it can be tested and its quality assessed. In meta-heuristics, the emphasis is on performing a deep exploration of the most promising regions of the solution space. The quality of solutions produced by these methods is much higher than that obtained by classical heuristics. Some examples: Ant Algorithms [10], Constraint Programming, Simulated Annealing [11], Deterministic Annealing, Genetic Algorithms, PSO [12], Tabu Search.

III. Rich Vehicle Routing Problems

Some very frequent attributes [13] regarding Rich Vehicle Routing Problems (VRP) are: route length and duration, multi-depot, periodic, time-windows, mixed fleet, multi-compartment, backhauls, pick-up and deliveries, location routing. Classification [14], [15] of VRP:

Capacitated VRP - CVRP: Every vehicle has a limited capacity.

VRP with time windows - VRPTW: Every customer has to be supplied within a certain time window [16]. Each customer provides a time frame within which a particular service or task must be completed, such as loading or unloading a vehicle. If the vehicle arrives too early, it must wait until start of service is possible. Some VRPTW models (soft time window models) allow for early or late window service, but with some form of penalty, others have focused on the hard time window models.

Multiple Depot VRP - MDVRP: The vendor uses a number of depots to supply the customers. Each vehicle originates at one depot, services the customers assigned to that depot, and returns to the same depot. The objective of the problem is to service all customers while minimizing the number of vehicles and travel distance. A solution is feasible if each route satisfies the standard VRP constraints and begins and ends at the same depot.

VRP with Pick-Up and Delivery: Customers may return some goods to the depot.

Split Delivery VRP: The customers may be served by different vehicles.

Stochastic VRP: Some values (like number of customers, theirs demands, serve time or travel time) are random.

Periodic VRP - PVRP: The deliveries should be done repeatedly in previously specified days, i.e. one has to plan over several days (planning horizon of T days). Each customer has frequency of visit requirements (e.g., k out of T days). Visits to customers must occur on allowed k-day combinations. Acceptable combinations of visits called patterns are created for each client. The goals are: Each customer must be assigned to a single depot and a single pattern; Routes must be constructed for each depot and day; The total cost of all routes should be minimized. Rolling-horizon procedure is described in [17].

In MDPVRPTW context, a tour for each couple (day, depot) needs to be optimized. The proposed model further enables to specify cases with requirements of multiple replenishments of some of the customers (ATMs) daily, while other customers may need only one replenishing in several days.

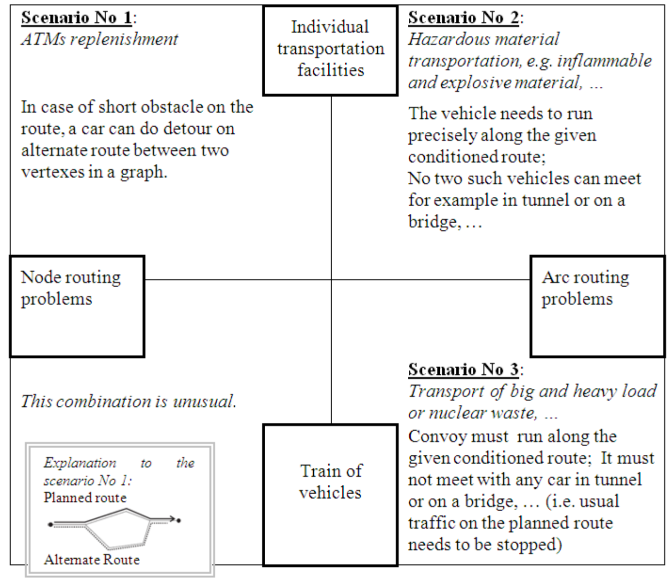

Fig. 2 Examples of Node and Arc routing problems for individual cars and for train of vehicles

It is important to highlight the complications introduced by the minimum days-of-service constraints. The problem exhibits strong links across multiple periods, not only because of inventory costs induced by the day-of-week delivery pattern for an individual customer, but also because the customer's days-of-service constraint depends upon the delivery patterns of the other customers. Actually no efficient exact methods are known for PVRP, therefore different heuristics are used. Hybrid genetic algorithms exist for VRP, VRPTW, MDVRP; few on periodic problems.

The *Inventory Routing Problem* (IRP) involves the repeated distribution of a single product from a single facility to n customers over T days. Customers consume the product on a daily basis and maintain a small, local inventory. The objective is to minimize the sum of transportation and inventory-related costs (stock-outs can be costly). This is a very rich multi-period problem. One must first assign customers to patterns (certain days of the time period) and then find for each day routes servicing the customers scheduled on that day. One seeks to minimize total distance travelled during the time period. As an example, a waste management company has to assign customers to certain days of the week and then create daily routes.

Problems described above belong to *Node routing problems* because all customer demands are located at the nodes of an underlying graph or network. In *Arc routing problems*, the demands are associated with the links between the nodes, called edges or arcs (in the undirected resp. directed case) [18]. In Fig. 2, classification of similar transport scenarios is characterized according to Node and Arc routing problems. A workflow for business processes based on described routing scenarios will be created and depicted later, in Section VI.

Routing problems represent roads in the underlying road network. Arc routing problems arise naturally in applications such as garbage collection, mail delivery, snow clearing, meter reading, school bus routing, police patrols, and winter gritting. In these cases, a service must be carried out which involves the vehicle travelling a road section while performing the required service. This is often done at a different speed compared to a speed of a vehicle simply travelling along one of the roads without servicing it.

Dynamic or real-time VRP: Models discussed so far have been suitable for planning the operations of a vehicle fleet in advance. Nevertheless, models are also being developed to assist in the real-time management and control of a distribution process.

One of the possible approaches to dynamic routing is based on usage of multi-agent systems. As an example, in the agents team used for solution of single source shortest path problem based on road network hierarchy [18] appeared graph constructing agents, agents interacting with the system user, etc. Other significant term in the domain of multi-agent systems is the environment, in which are the agents located. It includes vehicles, roads, road signs and signals as well as important places usually named points of interest (POI). Two assumptions were made in [19] for building highway hierarchies graph: (1) system must be able to take into account the user's demands, preferences, and environmental conditions; (2) where possible, computations should be done concurrently.

The consideration of environmental costs is essentially changing the transportation policy in developed countries, especially those within the European Union. The reduction of total travel distance will in itself provide environmental benefits due to the reduction in fuel consumed and in the resulting pollutants [20]. The same holds for avoiding unexpected traffic congestion due, for example, to an accident. A potential for such benefits can arise from the use of dynamic or real-time models to manage a distribution activity. Similarly, a multi-criterion optimization of VRP for transport of hazardous material minimizes risk on roads, as well as the transport cost. Implementation of these models requires real-time information on the locations of the vehicles and on current traffic conditions, and reliable communication channels between a management and drivers.

To be effective, dynamic VRP must rely on up-to-date information. One type of dynamic model may consider new customer orders that arise after the routes had been initially planned. In the light of this information, the vehicles are re-routed so as to reduce costs and meet customer service time windows. In order to serve the immediate requests, online algorithms working in real-time must be employed. Generally, the more restricted and complex the routing problem is, the more complicated the insertion of new dynamic customers will be.

The *time dependent VRP* consists in optimal routing of a fleet of vehicles in cases when the travelling times between nodes depend on the time of the day the trip on that arc was initiated. The optimization is based on searching the solution minimizing the number of tours (the number of vehicles used) and the total travelling time. The travelling time is calculated knowing the departing time and an accurate estimate of the average speed of the vehicle while travelling on the arc. This version of the VRP is motivated by the fact that traffic congestion on popular routes will cause delays at peak times. By minimizing the total travelling time, the solutions produced will tend to direct vehicles to roads where they can travel at a faster speed instead of being caught in congestion.

Even if some of the solutions would imply a greater total travel distance, travelling in shorter time and at the best speeds will lead to overall environmental benefit.

The proposed model specifically accounts for effects of different delivery patterns. In contrast to many IRP models, the model directly addresses a multi-period problem with time-varying demand that may need to be satisfied by more than one shipment during the horizon.

IV. Vehicle Routing Problem's Formulation

The VRP is a combinatorial problem whose ground set is the edges of a graph G(V,E). The notation:

G = (V, E), where

$V = \{v_0, v_1, \ldots, v_n\}$ is a vertex set; v_0 denotes a depot

$E = \{(i, j) : i, j \in V, i \neq j\}$ is an edge set

C … matrix of non-negative costs or distances (travel time) c_{ij} associated with every edge $(i, j) \in E$

q … vector of customers demands

R_k is the route for vehicle k

m is the number of vehicles

$s_i \geq 0$ is a service time (duration) required by a vehicle to unload the quantity q_i at place v_i

A feasible solution is composed of:

- Routes $R_1, \ldots R_m$ which are partitions of vertex set V
- Permutations P_i of R_i specifying the order of customers on route i

The cost of a given route R_i is given by:

$$Cost(R_i) = \sum_{i=0}^{m} c_{i,i+1} + \sum_{i=1}^{m} s_i$$

A route Ri is feasible if the vehicle stops exactly once at each customer and the total duration of the route does not exceed a specified bound D_k, k = 1, … , m.

In VRPs, the planning period is typically a single day. In the case of the PVRP, the classical VRP is generalized by extending the planning period to T days.

Each vertex $i \in V$ has a demand $q_i \geq 0$ on each day of the planning horizon of T days, and requires a fixed number of visits f_i to be performed according to one of the allowable visit-day patterns in the list Z_i (pattern represents the days the associated customer receives a visit).

The objective is to minimize the vehicle fleet and the sum of travel time needed to supply all customers. A solution is feasible if all constraints of VRP are satisfied. During the T-day period, each customer must be visited at least once.

In the model of PVRP, the daily demand of a customer is always fixed. In proposed model of ATM cash replenishment, the daily demands of customers (ATMs) are varying. Forecasting is based on historical data.

The PVRP can be seen as a problem of generating a group of routes for each day so that the constraints involved are satisfied and the global costs are minimized.

PVRP can also be seen as a multi-level combinatorial optimization problem: In the first level, the objective is to generate a group of feasible alternatives (combinations) for each customer. For example, if the planning period has T = 3 days $\{d_1, d_2, d_3\}$, then the possible combinations are: 0→000, 1→001, 2→010, 3→011, 4→100, 5→101, 6→110, 7→111. If a customer requests two visits, then this customer has the following visiting alternatives: $\{d_1, d_2\}$, $\{d_1, d_3\}$, and $\{d_2, d_3\}$. In the second level, one of the alternatives for each customer has to be selected. In the third level, the vehicle routing problem is solved for each day.

In VRPTW a time window is associated with each customer defining an interval wherein the customer has to be supplied. The objective is to minimize the vehicle fleet and the sum of travel time and waiting time needed to supply all customers in their required hours. Each vertex $i \in V$ has a time window $[e_i, l_i]$, where e_i is the earliest time service may begin and l_i is the latest time.

PVRPTW can be seen as the problem of generating at most m vehicle routes for each day of the planning horizon, to minimize the total cost over the entire planning horizon, such that (1) each vertex i is visited required number of times, corresponding to a single pattern of visit-days chosen from visit day alternatives Z_i and is serviced within its time window, (2) each route starts at the depot, visits the vertices selected for that day and returns to the depot after a duration (travel time) not exceeding D.

Decision variables:

- route selection:

$$r_{ijk}^{t} = \begin{cases} 1 \; if \; vehicle \; k \; traverses \; edge \; (i,j) on \; day \; t \\ 0 \; otherwise \end{cases}$$

- pattern selection:

$$u_{iz} = \begin{cases} 1 if \; pattern \; z \in Z_i \; is \; assigned \; to \; ATM \; i \in V \\ 0 \; otherwise \end{cases}$$

- pattern assignment:

$$a_{zt} = \begin{cases} 1 \; if \; day \; t \in T \; belongs \; to \; pattern \; z \\ 0 \; otherwise \end{cases}$$

- further requirement: service starting time at the next ATM on the given route needs to be greater (or at least equal) than service starting time plus service duration time at the previous ATM plus travel time.

The PVRPTW can be formulated as minimization of

$$\sum_{t \in T} \sum_{(i,j) \in E} \sum_{k \in K} c_{ij} r_{ijk}^{t} \quad (1)$$

s.t.

$$\sum_{z \in Z_i} u_{iz} = 1, \;\; \forall i \in V \quad (2)$$

$$\sum_{k \in K} \sum_{j \in V} r_{ijk}^{t} = \sum_{z \in Z_i} u_{iz} a_{zt} \;, \forall i \in V, t \in T \quad (3)$$

$$\sum_{k \in K} \sum_{j \in V} r_{0jk}^{t} \leq m, \;\; \forall t \in T \quad (4)$$

The objective function (1) minimizes the total travel cost. The constraint (2) specifies that a pattern is assigned to each ATM. The constraint (3) specifies that each ATM is visited on the days given by the pattern. The constraint (4) guarantees that the number of used vehicles is at most m. To complete the given formulation, one has to specify constraints on time

Visit day	1.	2.	3.	4.	5.	6.	7.	8.	9.
$b = 1$	0	0		0	0		0	1	
$b = 2$	0	0		0	0		1	0	
$b = 3$	0	0		0	0		1	1	
$b = 4$	0	0		0	1		0	0	
…									
$b = 18$	0	1		0	0		1	0	
$b = 19$	0	1		0	0		1	1	
…									
$b = 27$	0	1		1	0		1	1	
$b = 28$	0	1		1	1		0	0	
…									
$b = 47$	1	0		1	1		1	1	
$b = 48$	1	1		0	0		0	0	
…									
$b = 63$	1	1		1	1		1	1	

Fig. 3 Patterns represent the days (in horizon T=3) the associated customer receives a visit

continuation based on service starting times, service duration times, and travelling distances on the routes.

V. The Proposed Meta-Heuristic

In the described model, there are 3 depots and 120 ATMs. The locations of ATMs are taken from Google maps of town Bratislava with its surroundings. The number of used vehicles is not constrained, but the aim is to keep it minimized. Each vehicle is supposed to run only one route per day. Any route can start in one of the 3 depots (while several routes can start in the same depot, there also can be a depot where no route starts). An individual for the proposed genetic algorithm corresponds to a feasible or infeasible solution to the MDPVRPTW, which specifies: the pattern assigned to each customer, the number of routes, and the delivery order within each route.

Not only deficit of cash in ATMs but also the acquired surplus money in ATMs is diseconomy. Boxes carrying money should return to a bank with as little surplus as it is possible (because of the cost of the money). Time window constraints for the ATMs are stated based on historical data of withdrawals from each of the ATMs (based on locations in city centre or in suburb and other parameters such as events organized in close vicinity).

The problem to be solved using GA is encoded as a chromosome that consists of several genes [21], [22]. The solution of the problem is represented by a group of chromosomes referred to as population. During iterations of the algorithm, the chromosomes in a population will undergo one or more genetic operations such as crossover and mutation. The result of the genetic operations becomes the next generation of the solution. This process continues until either the solution is found or a certain termination condition is met.

The basic assumption is that each vehicle works one shift (8 hours) per day. Some of the vehicles may work in morning shift from 6 a.m. till 2 p.m., and some of them in afternoon shift from 2 p.m. till 10 p.m.

Patterns in Fig. 3 represent the days (divided into 8 hour

Customer	i = 1.	2.	3.	4.	5.	6.	…
Pattern chr	b = 2	**18**	**47**	**2**	**2**	**63**	**…**
	000010						

Route chr	**A**	15	7	12	26	…	**B**	**3**	**22**	**14**	…

Fig. 4 Representation of individual in GA
a) pattern chromosome (above),
b) route chromosome (below)

long time intervals) in which the associated customer receives a visit. For example, the pattern number 1 specifies that the ATM to which the pattern will be assigned requires cash replenishment only the third day in the afternoon. The pattern number 63 specifies that the ATM requires replenishing each day two times. The third 8 hour long time interval (night) will not be used for replenishing.

A. Individual Representation

Each individual is represented by two chromosomes: the first addressing the pattern-to-customer assignments, the second corresponding to the routes performed on each day of the planning horizon.

Pattern chromosome is associated with n customers (see Fig. 4a). Each entry i of this chromosome is a positive integer *b* that describes the pattern assigned to customer i. The binary representation of b stands for the days (more precisely parts of the days) the associated customer receives a visit. For each day in the planning horizon, a group of routes services customers on that day.

Route chromosome corresponds to the combination of the set of vectors, each representing the ordered sequence of customers for one route of a day. Each of the routes starts and ends in the same depot (see Fig. 4b).

B. Clustering and Routing

In the proposed model, cluster first - route second scheme is used:

- Customers (ATMs) are sorted in increasing order of the angle they make with the depots.
- Sequence of n customers is divided into clusters of ATMs surrounding each of the depots.
- Some of the customers the positions of which are near the clusters boundary are allowed to be serviced by vehicles starting from both relating depots.

Routing is performed iteratively for each cluster. Another possibility is Route first - cluster second scheme.

In case of too narrow TW, the sorting of customers into groups belonging to depots doesn't provide faster computation, as many of ATMs will be served from other depot than initially assigned.

C. Evaluation

Given a solution sol, denote the total travel cost of its routes ttc(sol),
d(sol) … total violation of route duration (computed on a route basis with respect to bound D)
w(sol) … total violation of time window restrictions
deficit(sol) … total deficit of cash
surplus(sol) … total cost of acquired surplus money in ATMs

Solutions are evaluated according to the fitness function:

$$f(sol) = ttc(sol) + \alpha\, d(sol) + \beta\, w(sol) + \gamma\, deficit(sol) + \delta\, surplus(sol)$$

where α, ß, γ, δ are penalty parameters. Parameters α and ß are repeatedly adjusted so as to positively influence the total travel cost of the routes. Parameters γ and δ are properly set constants. Parameter α amplifying the violation penalty of route duration needs to be set in accordance with cost of vehicle services per day (if this cost is high, a small violation of the route duration may be profitable with respect to fitness of the individual). Parameter ß amplifying the violation penalty of time window restrictions needs to be set in accordance with distance which can be passed through in a time equalling to total violation of TW (based on the average speed of the vehicles in the area), as shorter routes with high TW violations should not be profitable.

After random creation of the initial population, fitness of each individual in the population for the current generation is evaluated, using parallel computation. Selection, crossover and mutation operators are used in the proposed algorithm.

VI. SIMULATION

Parallel computing technologies enable engineers to accelerate solutions of their computational problems by using multiple hardware resources. The ability to solve very large problems by scaling computer programs so as to be run on multi-core workstations, clusters, grids, and clouds can help engineers gain significant research and competitive advantages. Genetic algorithms are generally able to find good solutions in reasonable amount of time but as they are applied to harder and bigger problems, there is an increase in the time required to find adequate solutions. As a consequence, there have been multiple efforts to make GAs faster and one of the promising choices is to use parallel implementation. The proposed genetic algorithm is implemented in Matlab [23], [24], [25], [26].

MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. It is halfway between a programming language (a user must do everything) and a menu-driven application (the user only makes high level decisions). The MathWorks parallel computing tools let users develop Matlab applications that can work in a variety of environments, from a multi-core desktop to computer clusters and grids. MATLAB Distributed Computing Server (MDCS) enables users to execute the same MATLAB codes in the grid that were executed on the desktop.

MATLAB also provides integration with grid services. Issues of running parallel MATLAB on EGEE (Enabling Grids for E-sciencE) grid are described in [27].

A. Output of the simulation (first example)

In this example, time windows specified for ATMs equal to one working shift of the vehicles, i.e. 8 hours. An average speed of the vehicles is supposed to be 45 km/hour, and

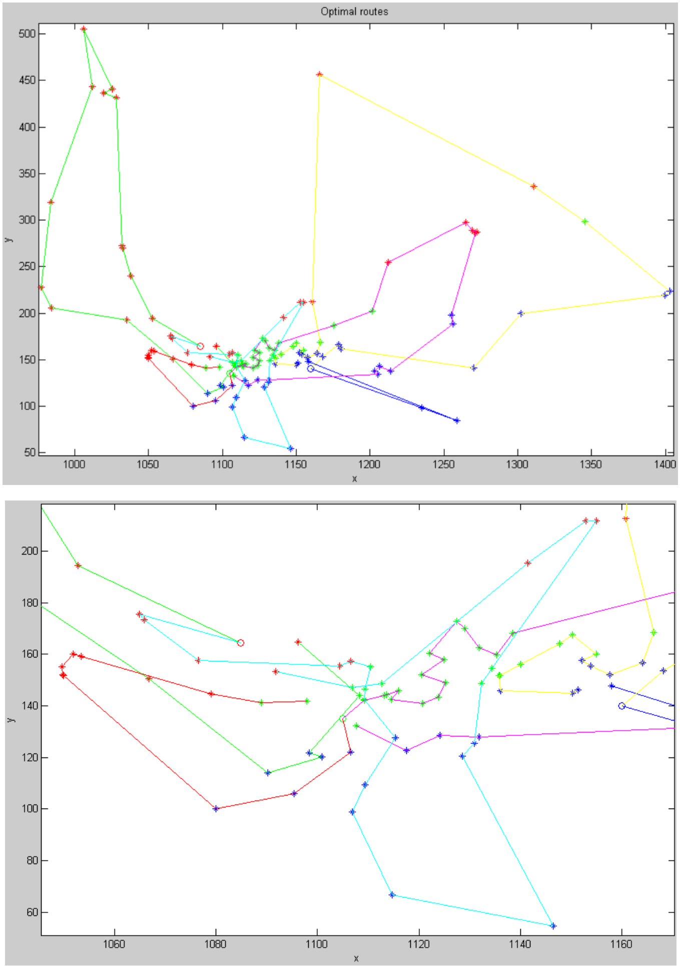

Fig. 5 Locations of 3 depots (circles) and 120 ATMs (stars), and optimal routes for 6 vehicles
(zoom into the area with short distances is given below)

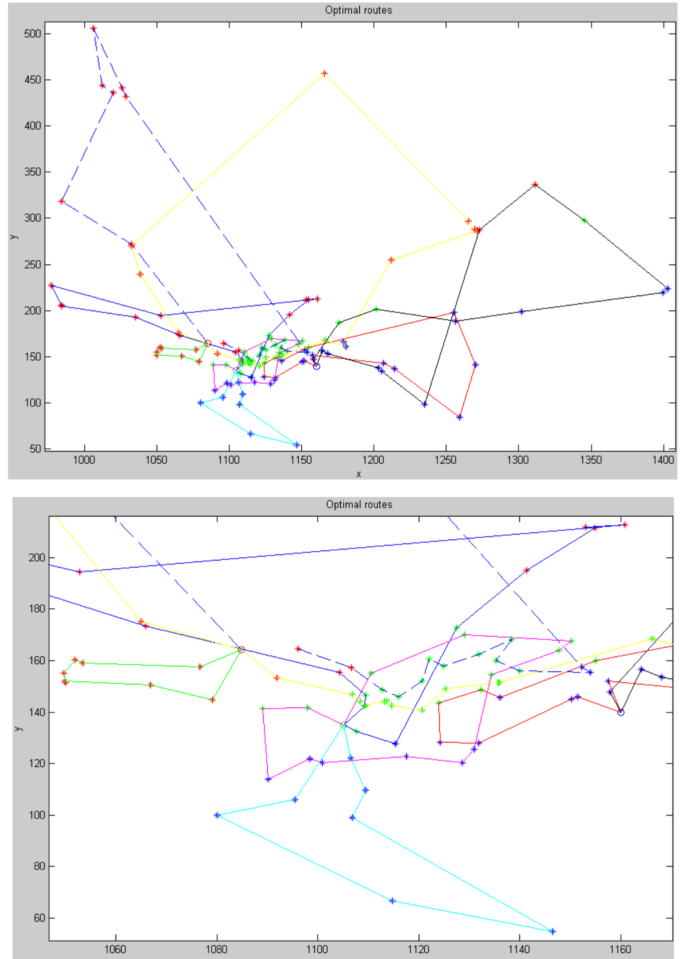

Fig. 6 Locations of 3 depots (circles) and 120 ATMs (stars), and optimal routes with fulfilled time window constraints for 8 vehicles in 1 day (zoom into the area with short distances is given below)

average service duration is set to 10 minutes. Control parameters used for the run:

- population size = 5000
- number of generations = 2000
- probability of crossover = 0.6

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Number of depots: 3 (labelled as 1, 2, 3)
Number of ATMs: 120 (labelled as 4, 5, … , 123)
Number of routes: 6
Vehicle no 1 (blue route) = 1, 28, 119, 45, 1
Vehicle no 2 (green route) = 3, 78, 73, 113, 104,
102, 101, 103, 99, 115, 100, 116, 71, 72, 75, 79,
66, 82, 74, 92, 83, 98, 12, 61, 3
Vehicle no 3 (red route) = 2, 89, 85, 4, 76, 50, 67,
69, 77, 70, 18, 10, 2
Vehicle no 4 (yellow route) = 1, 31, 36, 30, 120,
117, 122, 121, 112, 106, 111, 55, 47, 29, 34, 22,
14, 32, 123, 64, 54, 42, 40, 39, 35, 44, 53, 1
Vehicle no 5 (magenta route) = 2, 13, 19, 24, 6, 41,
5, 27, 37, 16, 65, 59, 51, 60, 62, 25, 57, 63, 46,
11, 114, 108, 109, 110, 107, 118, 105, 33, 48, 49,
38, 84, 95, 93, 87, 2
Vehicle no 6 (cyan route) = 3, 68, 81, 80, 8, 26, 9,
17, 23, 91, 90, 97, 86, 96, 94, 88, 43, 7, 58, 52,
56, 15, 20, 21, 3
```

Total distance travelled is 460 km. For illustration, sub-optimal routes for one day are given in Fig. 5.

B. *Output of the simulation of example with TW*

In this example, time windows prescribed for 25% of ATMs are from interval 2-4 hours, TWs for the other ATMs remain one working shift long (same as in the first example).

```
Number of depots: 3 (labelled as 1, 2, 3)
Number of ATMs: 120 (labelled as 4, 5, … , 123)
Number of routes: 8
Vehicle no 1 (blue route) = 2 (start time 6:00), 87,
91, 51, 56, 58, 52, 55, 78, 71, 72, 75, 66, 79, 81,
8, 17, 13, 2
Vehicle no 2 (green route) = 3 (start time 6:00),
70, 74, 82, 50, 76, 67, 69, 77, 80, 3
Vehicle no 3 (red route) = 1 (start time 16:00), 34,
48, 33, 119, 120, 118, 32, 35, 43, 27, 95, 84, 44,
53, 1
Vehicle no 4 (yellow route) = 3 (start time 6:00),
68, 73, 113, 111, 108, 109, 107, 114, 36, 30, 47,
40, 39, 37, 5, 41, 24, 19, 23, 12, 20, 21, 3
Vehicle no 5 (magenta route) = 2 (start time 10:00),
9, 60, 64, 123, 54, 7, 88, 94, 93, 83, 98, 92, 18,
10, 2
Vehicle no 6 (cyan route) = 2 (start time 6:00), 85,
4, 86, 96, 97, 90, 89, 2
Vehicle no 7 (black route) = 1 (start time 6:00),
29, 31, 49, 38, 28, 110, 106, 112, 121, 122, 117,
105, 11, 46, 45, 1
```

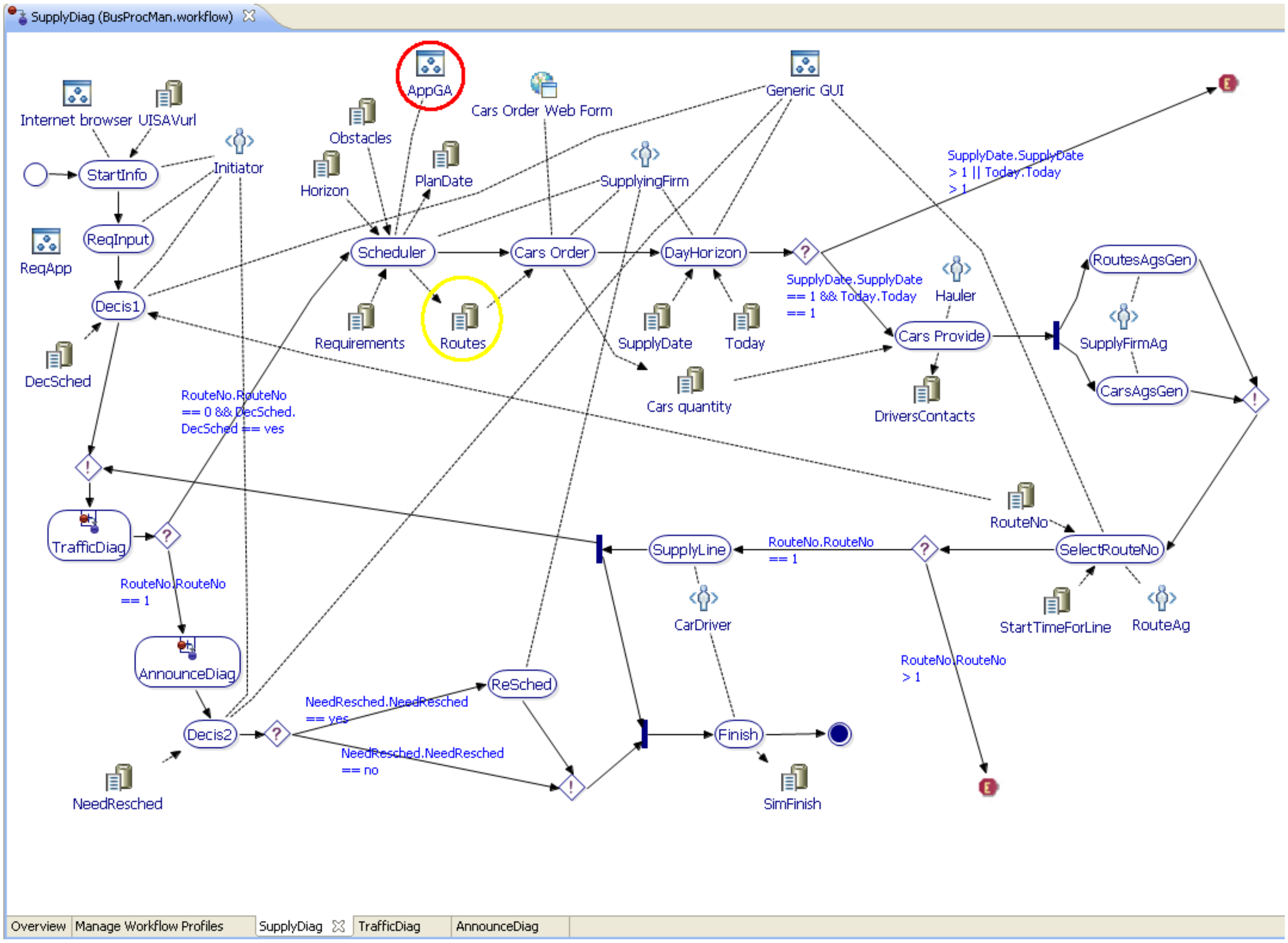

Fig. 7 Supply diagram containing the routing algorithm invocation

`Vehicle no 8 (dashed blue route) = 3 (`**`start time 6:00`**`), 104, 116, 103, 101, 100, 115, 99, 102, 14, 22, 42, 25, 57, 63, 62, 65, 59, 16, 6, 15, 26, 61, 3`

As an illustration, sub-optimal routes for one day are depicted in Fig. 6. Total distance travelled is 541 km and all time windows constraints are fulfilled.

C. Proposal of a workflow for the routes scheduling

Cooperative information systems are multi-agent systems [5] with organizational platform and database layer conforming to open environment consisting of a different kinds of information sources. Mobility of actors introduces other new challenges to workflow systems development. Context-aware voice user interfaces [6] are one of promising approaches to optimize business processes and to reduce costs is business process management (BPM). The development of multimodal applications is complex and time-consuming, since each modality has unique characteristics.

There is not much work concentrating on the integration of context-awareness and workflow systems. Currently, there is not much research trying to combine workflow engines and voice user interfaces.

For our purposes, a workflow is a series of actions performed by a set of actors. The proposed workflow is created in Java Workflow Tooling (JWT) [28], which is an Eclipse based business process modelling suite and the processes are simulated using the AgilPro simulator [29].

Supply diagram for BPM with Traffic and Announcement sub-diagrams included is depicted in Fig. 7. The proposed GA for periodic routing is highlighted by a red circle in the workflow. Data regarding the optimal routes generated by a proposed GA are highlighted by a yellow circle. Details of ATM cash replenishment scenario are described in Fig. 1, and details of similar BPM scenarios are described in Fig. 2 in previous sections. Properties of these similar BPM scenarios were also taken into account during creation of the Supply diagram to enable a smooth change of workflow to comply with any similar scenario.

Rescheduling of planned routes, e.g. in case of an accident on the planned route, is proposed in traffic sub-diagram. Properties of voice communication about actual obstacles on roads as well as communication regarding a need for rescheduling in case of long term obstacles and its actors are described in announcement sub-diagram.

Details of the traffic sub-diagram for BPM can be seen in Fig.8. Top part of Fig. 9 contains the announcement sub-

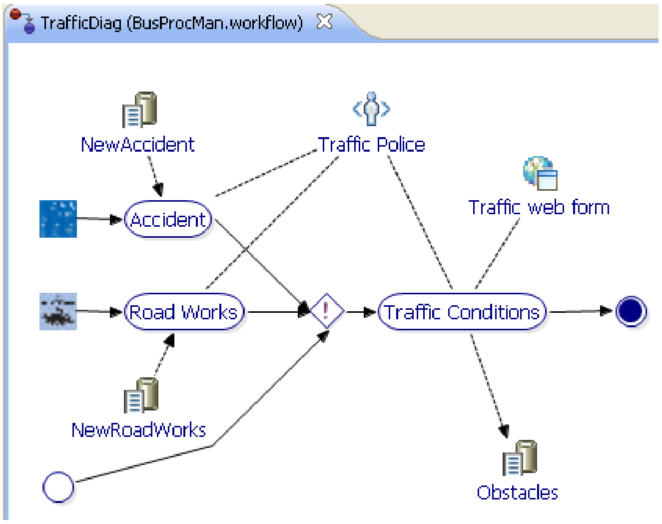

Fig. 8 Traffic sub-diagram generating data on obstacles on planned routes

diagram for BPM, and a step of its simulation in AgilPro simulator is given below.

Further work on integration of context-awareness, mobility, voice user interfaces, and routing optimization for BPM with multi-agent systems and workflows is planned. In this sub-section, starting proposals and achievements in this field of research were presented.

VII. Conclusion

Deriving the optimal cash deployment strategy for a network of ATMs involves the analysis of logistics costs, inventory policies as well as of the routing of replenishment vehicles. The optimal cash deployment strategy focuses on the reduction of cash-related expenses while providing that ATMs do not run out of cash. Shorter routes with high time window constraints violations are not always the best solution, as not only deficit of cash in ATMs but also the acquired surplus money in ATMs is uneconomical. The periodic vehicle routing problem can be seen as a problem of generating a group of routes for each day of a planning horizon so that the constraints involved are satisfied and global costs are minimized. Furthermore, the proposed model enables to specify cases with requirements of multiple replenishments for some of the customers (ATMs) daily, while other customers may need only one replenishing in several days. Parallel computing technologies offer engineers the means to accelerate solutions of their computational problems by using multiple hardware resources. The ability to solve very large problems by scaling computer programs to run on multi-core workstations, clusters, grids, and clouds can help engineers gain significant research and competitive advantages.

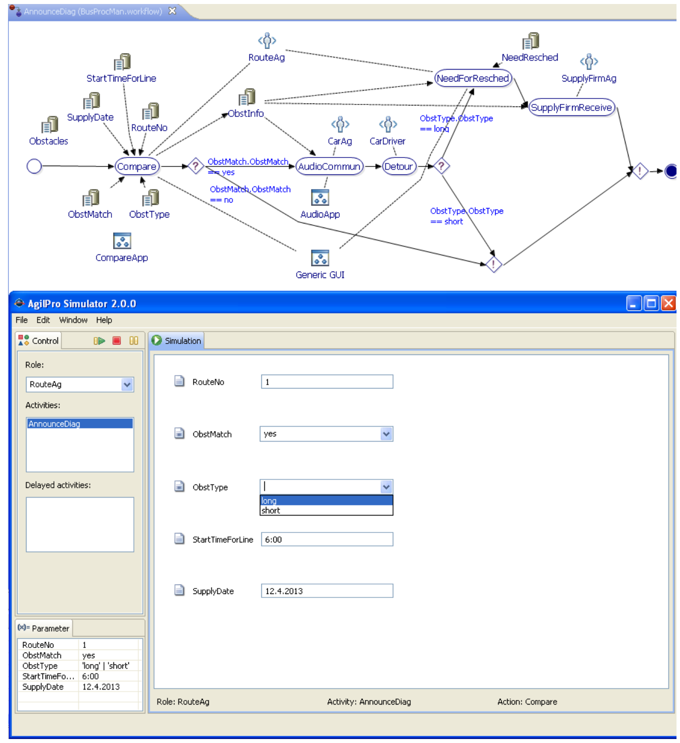

Fig. 9 Announcement sub-diagram containing the agents voice communication's properties and actors (top) and its simulation in AgilPro simulator (bottom)

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