A TECHNOLOGICAL PLATFORM FOR DESIGNING REAL-TIME DECISION TOOLS IN TRANSPORTATION LOGISTICS

J.J. Ramos D. Guimarans M.A. Piera
Department of Telecommunication and System Engineering - Logisim
Universitat Autònoma de Barcelona
08193 Bellaterra, Spain
JuanJose.Ramos@uab.es, Daniel.Guimarans@uab.es

A. Guasch
Dpt. of System Engineering and Automatic Control - Logisim
Universitat Politècnica de Catalunya
08028 Barcelona, Spain
MiquelAngel.Piera@uab.es, Toni.Guasch@upc.es

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ABSTRACT

During the last years, the transportation industry has been involved in important new challenges to cope the changes in production and logistical systems. Just-In-Time procurement and quick and efficient consumer response are some of the reasons why the transportation industry has recognized the need to incorporate new information technologies such as Global Positioning System (GPS), Electronic Data Interchange (EDI) and Internet.These technologies can enhance the capabilities to optimize the transport operations since they provide the necessary information required to perform real-time decision making. This paper presents the laboratory environment that is being developed for the design of real-time decision tools for the transportation industry.

INTRODUCTION

In a context of competitive and ever more global industrial production and in an economy oriented to services, the availability of transport units that can respond efficiently will be a very important factor for the competitiveness of the industrial and service companies. The transport logistics is a typical example of a highly complex and time-critical business environment. A high number of organizational units have to achieve an optimal allocation of resources,while coping with dynamically changing requests, conditions and constraints. This class of logistics problem is usually known as the vehicle routing problem (VRP). A key issue in VRP is the cost-efficient management of vehicle fleet providing the transport operations. The interest is to minimize the cost expressed as a combination of distance, time and/or money.

The transport of goods in metropolitan areas deserves special attention due to the high number of inefficiencies currently present. The consequence of these inefficiencies is serious in terms of its contribution to the increasing congestion in metropolitan areas. The congestion has become an important concern to policymakers in recent years (Wachs 2002). Not only are commuters stuck in traffic for longer periods of time at rush hour, but traffic congestion is seen as a contributor to declining air quality. Transport optimization in metropolitan areas have the potential of reducing the transportations costs (Papows 2001), reduce traffic congestion and increase the reliability of this service. Emergency fleet management is an example where the service time becomes a major challenge. The coordination of the three main emergency services, i.e. Police Service, Medical Service and Fire Service, is a key issue to ensure an effective intervention in road accidents or medical emergencies.

The high complexity of VRP is thus a prime target for optimization technologies. Real-Time Decision Tools for the VRP must combine GPS information, GIS technology, on-line electronic data interchange, Web-servers and efficient optimization algorithms in order to cope with the current needs. These new technologies open the door to the design of planning systems able to make this information profitable. This paper presents a technological platform which integrates these new technologies to support the design of real-time decision tools in transportation logistics. This platform has a distributed computing architecture in order to deal with the different problems falling in the VRP category. The decision tools should react in real-time in metropolitan areas where the duration of the trips are relatively short and every new transport operation should be served in very short time periods. The paper presents a two-phases approach to face real-world applications: the preprocessing phase where the geographical information is arranged according to the VRP problem to be solved; the optimization phase where resources are allocated and optimal routes are defined. Testing and improving those complex systems in a real environment is inefficient and expensive. The presented platform integrates a fleet simulation model which is able to represent the fleet transportation problems at different levels of complexity. Next section introduces the software architecture where the simulation environment provides the information of a transportation fleet. The following sections will describe the system model and the tools which process the geographical information required by the decision making tools, describing the basic characteristics of the optimization algorithms which are proposed to deal with the VRP problems. Some conclusions are pointed out at the final section.

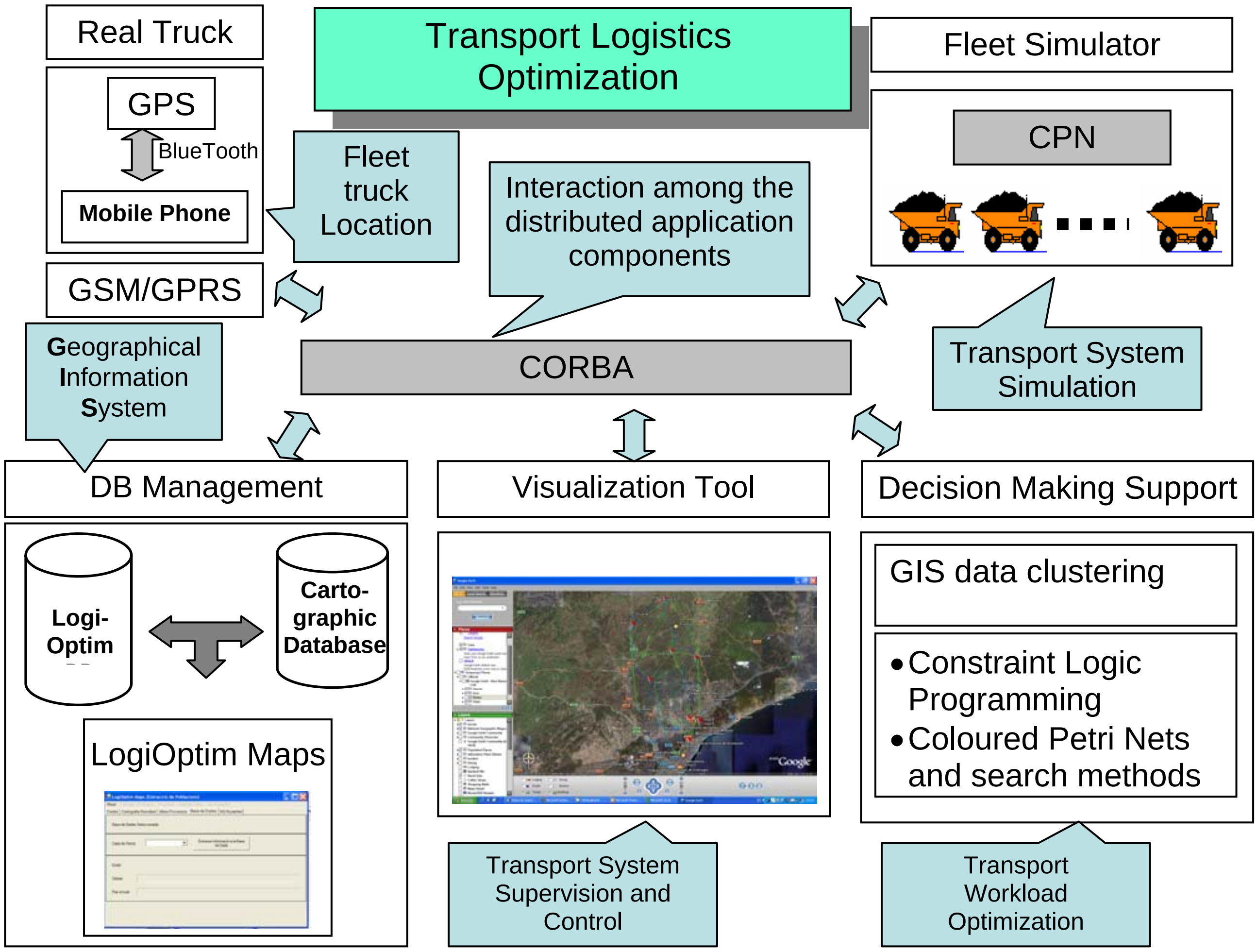

Figure 1: System Architecture

DISTRIBUTED PLATFORM ACHITECTURE

Because the project has a multidisciplinary approach the computer program architecture integrates different technologies, i.e. different software, programming languages and operative systems. Figure 1 illustrates the system architecture. The system involves five main modules: the Geographical Information System, the Fleet Simulator, the Decision Making Tools, the Visualization Tools and the vehicle localization system. The system has been designed as a distributed application based on CORBA (OMG 2004) to simplify the coordination and communications between the application modules. The complete modularity of this architecture also permits to replace modules answering to the simulation needs or to the fleet management case studies such as, for instance, freight transportation in metropolitan areas (Busquets et Al. 2005) or the emergency services management in road accident (Guimarans et Al. 2006).

The Geographical Information System (GIS) module manages all the static and dynamical data in the system. The static data is composed by the geographical data, provided by a cartographic database, and the filtered geographical data, which is extracted from the former and generates a representation of the roads and streets network according to the need of the decision making module. The dynamical data is composed by the fleet structure information (vehicle characteristics, state of vehicles, etc), the georeferenced position of each vehicle and the georeferenced position of the transport operations, as well as their characteristics, which depend on the VRP being solved. For instance, weight, dimensions and transport time windows constraints in freight transportation or the vehicles involved and number of injured victims in the emergency service management.

The Visualization module is a graphic application where the vehicle movements and the configured routes are represented on the map. Vehicle positions are generated and registered at the database by the Fleet Simulator module during the development stage and by the real vehicle positioning system, based on GPS and mobile communications, at the real operation case.

The Decision Making Support module has to find a solution for the problem, which falls into the VRP category (Bektas 2006). Near all the solution techniques for this problem are heuristics and metaheuristics because no exact algorithm can be guaranteed to find optimal solutions within reasonable computing time due to the NP-Hardness of the problem. More details on this module will be given

TRANSPORT FLEET MODEL

In this section, the basic characteristics of the transport system model are described. This model will be used to develop and test the optimization routines in order to evaluate the decision making performance. The simulation model has two main functionalities: generation of the work load (transportation orders) for the transport system and the simulation of the goods delivery routes assigned by the transportation optimization module.

The transport system model should be easily adaptable to the different applications of the vehicle routing problem (e.g. freight transportation or emergency service management). Hence, model development has not been guided by a particular routing problem configuration, which means that the model reflects the system structure (e.g. transportation resources, vehicle capacities, number of depots or transport network characteristics) in such a way that the model can be parameterized to suit with the VRP problem. Therefore, the use of a modelling methodology able to represent in a clear way both the system structure and its dynamic behaviour becomes advisable. Coloured Petri Nets (CPN) have proven to be successful tools for modelling the characteristics for any type of discrete event oriented system. The CPN formalism shows several advantages such as the conciseness of embodying the static structure and the dynamics, the availability of the mathematical analysis techniques as well as its graphical nature (Jensen 1997, Silva and Valette 1989, Zimmerman et al. 1996).

The state of the transport system is determined by the fleet state (load and position of every vehicle), the transportation orders and the routes configured by the optimization module. Vehicles, transportation orders and routes are represented by the CPN tokens. Colour sets are used to characterize the different VRP problems to be faced:

- Vehicles: the colours represent both their static attributes (e.g. weight and volume capacity, costs or maximum velocity) and dynamic attributes (e.g. current load and state, current GPS position, current velocity or assigned route).
- Transportation orders: the colours represent the load characteristics, origin and destination as well as delivery constraints such as the delivery time window.
- Routes: they are characterized by the number of destination points where goods should be loaded or unloaded. The routes are configured by the optimization module.

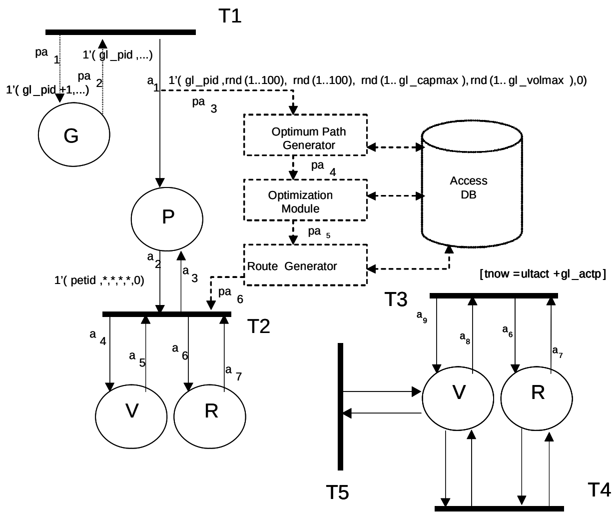

Figure 2: CPN model of the transport order generation, vehicle routing assignments and fleet movements

The CPN model is shown in Figure 2 and Table 1 outlines the place and transition descriptions. Transportation orders are generated according to a stochastic model at initial time, although new orders may arrive at any time afterwards (transition T1 is fired). Two parts are distinguished in the system dynamics represented by the model: the generation of the transportation orders and the simulation of the fleet movements across the road/street network.

Table 1: Description of Places and Transitions

Place	Description	Transition	Description
G	Generation of the transportation orders	T1	Arrival of new transportation order
P	Transportation order state.	T2	Assignment of a new transportation order to a vehicle.
V	It indicates the state of vehicles.	T3	Its firing updates the position of the fleet vehicles and its implications over the followed routes.
R	It represents the routes configured by the optimization module.	T4	Load/unload operation
		T5	Incidence event

Processing a transportation order basically consists of deciding which vehicle is assigned and, so that, on which route the order is delivered. These decisions are made by the application module which is described in the next section. The fleet movements are determined by transition T3. When T3 is fired the fleet state is changed and the transportation orders are served as the vehicles arrive to the load/unload points (transition T4). Different types of incidences can be simulated by firing transition T5 (e.g. vehicle breakdown or loose of the vehicle GPS location). All the information generated by the simulator is stored at the GIS module (see Figure 1) since all the system data is shared by the application modules by accessing to the data bases. The Arena simulation tool (Kelton 1998) has been used in this project to build the simulator.

DECISION MAKING TOOL

The objective of the VRP is to deliver a set of customers with known demands on minimum-cost vehicle routes, frequently, originating and terminating at a depot. The VRP problem falls into the category of NP complete problems. A two phases approach is suggested to make decisions according to the optimization criteria. The first phase pre-processes the GIS data in order to reduce the significant computing burden when shortest paths have to be calculated in order to find optimal routes. GIS data is clustered according to the needs of the VRP to be solved (single or multiple depot, homogeneous or heterogeneous fleet, routes with single or multiple visits, etc) while keeping exact information about travel time and costs between the pick-up/delivery points. The second phase solves the VRP problem with the geographical information provided at the first phase.

GIS data clustering process

The geographical information contained at the cartographical databases is needed to compute realistic travel time and costs. However, the huge amount of data provided by these databases would make the VRP intractable in a real-world case due to the computation time. For example, computing the shortest path between two points at the Barcelona metropolitan area (e.g. Barcelona city and surroundings have $3*10^5$ geographical nodes and edges) takes one second in a standard personal computer using a special purpose software available in the market. A workload of 100 pick-up and delivery operation will require the computation of 10.000 shortest paths between origin and destination points.

The application *Shortest Path Generator* (SPG) has been developed to prepare the proper geographical information for the optimization problem. A simplification of the information provided by the GIS is obtained by SPG representing the minimum cost paths among the relevant geographical nodes. These nodes

Figure 3: GIS data clustering for the emergency service management

represent either geographical points relative to the transportation orders, either vehicle current positions or relevant geographical points such as road junctions.

SPG generates two types of GIS data representation: a graph of shortest paths (used by the optimization module based on constraint programming) and the minimum distance matrix (used by the optimization module based on CPN and coverability tree evaluation). The reduced GIS representation depends on the VRP to be solved.

The emergency service management (Guimarans et Al. 2006) is seen as a multi-depot VRP with heterogeneous fleet. In order to reduce the computation time at the optimization phase, GIS information is preprocessed by classifying the GIS nodes according to distance and travelling time from the different depots. Thus, each node is only reachable by a vehicle whose base is located at the depot which minimizes distance and travelling time, creating a cluster-based structure, as shown in Figure 3. The goal of this geographic data rearrangement is to reduce the multi-depot VRP problem to a set of single-depot problems, where only one for each service has to be solved when an accident takes place. Therefore, variables' domains are reduced, improving the response time of the optimal solution search algorithm. To perform this pre-process, a common heuristic A* procedure is used to classify the geographic information into separated clusters. Moreover, a shortest path determination task is performed, so nodes are reordered into the cluster structure. Thus, when an accident notification is received, a shortest path approach from the depot to the accident scene is known, achieving an important calculation reduction. An uniform cost heuristic function is introduced in the clustering algorithm. The reason is that every single node is a potential accident node, so no particular direction may be pondered during the search. Each path is explored until the time service restrictions are not fulfilled, delimiting thus the cluster edge. The uniform cost heuristic never overestimates the real cost of getting from one node to another. This property guarantees the optimality of all paths included in a cluster and ensure that no optimal solution may be discarded during the search (Russell et Al. 2003). As the algorithm always explores nodes with minimum associated cost at each iteration, it is possible to guarantee that the corresponding determined path from the depot to any node in the cluster is minimum. Since any suboptimal path to a particular node has a larger cost than the optimal one, it can be demonstrated that the suboptimal path will never be explored and the optimal solution will be returned.

For the freight transportation in metropolitan areas such an efficient GIS representation to determine the shortest path graph can not be achieved. In this case, the pick-up and delivery customer locations are not known in advance so the GIS information must provide the means to compute every possible shortest path among every customer. A layered GIS graph structure has been built for this purpose by considering that many shortest paths will use the same main roads connecting the origin and destination points. The number of layered graphs is determined by the road network at the working geographical area. Firstly, main cities and surroundings connected by highways are detected. Then, city's nodes and edges are recursively clustered in districts, malls, residential suburbs according to the main connecting roads and avenues. The number of possible shortest path between costumers to be computed is significantly reduced with this layered GIS data clustering. For example, only 200 shortest paths (instead of the 10.000 required with GIS data flat representation) have to be computed if 100 pick-up operations in City A (100 from pick-up locations to the highway entry point) have to be delivered at City B (100 from the highway exit point to the delivery locations). Furthermore, the shortest path computation time is significantly reduced since the number of nodes/edges at the graph where they are computed is also lower. The Ant Colony approach (Dorigo et Al. 2003) is being used to obtain this layered representation of the GIS data. One interesting application of this information structure being explored is its application in the cluster-first/route-second heuristic approach to solve the VRP problem at the optimization phase (Dondo et Al. 2005).

Transport resource allocation

The optimization problem formulation varies depending on the VRP being faced. At freight transportation, the objective function will include the number of trucks needed to perform the requested transport operations and the constraints are the working hours, the resting periods and the delivery time windows among others. Two different approaches have been adopted to solve this discrete optimization problem, where the objective function is to minimize the transportation cost. The first approach is based on Constraint Programming (Marriott and Stuckey 1998). Two elements are combined in the constraint satisfaction problem: the model where the decision variables, the problem constraints and the objective function are defined; the solution search algorithm which selects a value in the domain of each constrained variable, so that all the constraints are satisfied. In order to solve this problem a commercial solver based on constraint satisfaction technology is used. The second approach combines simulation and search techniques. The transport system is modelled with Coloured Petri Nets (Jensen 1997) and its coverability tree is used to evaluate the reachable states from a given initial state. However, the coverability tree of a logistic system can grow exponentially with respect to the number of events that could be fired in parallel. Heuristic techniques are used to reduce the search space and to drive the system into a desired final state (Narciso et al. 2003).

In the emergency service management, the objective is to assign resources to accidents according to the implicit restrictions of the problem, which falls into the Constraints Satisfaction Problem (CSP) category. These constraints define that the maximum fixed response time may not be violated by the problem solution and no area must rest uncovered, affecting resources' allocation. Therefore, all resources of a particular depot may not be assigned to a single accident, since the second restriction would not be satisfied. Constraint Satisfaction Problem (CSP) techniques are used to find a feasible solution. System constraints are related to the available resources and specially to time windows. The information obtained at clustering stage is used to reduce the solution search space. Furthermore, an accident may be associated to a particular depot with a minimal computational cost, since either the accident location belongs to a specific cluster or the distance from the accident node to close clusters' edge may be easily calculated. Thus, the solution search is simplified to explore only nearby clusters, reducing the search space. In some cases (e.g. accident occurred in an isolated area, traffic jam, etc.), a solution fulfilling all the imposed constraints may not be reached. Thus, time constraints may be relaxed or weighted and minimizing the response time becomes an objective of the arising optimization problem. The main aim is to allocate resources satisfying all the imposed constraints except the response time restriction, which turns into an objective function.

In both classes of the outlined VRP problems, the information available during the transport system operation is dynamically changing. For example, not all accident variables are known until the first emergency unit arrives to the accident scene. Furthermore, the information may arrive from different sources, containing a large uncertainty. In the case of freight, new transport operations are continuously arriving, so the decision making tool must perform the proper route rescheduling. Moreover, roads state may change during operation from the moment a route is configured to its service ends, so shortest paths calculated at clustering stage may become non optimal. This situation may be determined using vehicles' GPS information, since their geographical position and movements are well-known. Thus, the corresponding route must be recalculated and, in some cases, resources should be reallocated. All this situations can be represented by the simulation model so the decision making tool can be properly designed and validated without the costs associated to the experimentation with the real-world transport system.

CONCLUSIONS

The paper presents a CORBA distributed environment which has been developed to assist in the design and validation of real-time decision tools in transportation logistics problems. Because of its modular and distributed structure, this technological platform can be easily adapted to deal with different VRP problems by introducing and/or replacing the different application modules. A fleet simulator is used to test the decision tools designed to tackle VRP optimization problems. The simulation model can be easily adapted to face different VRP problems. The decision making tools are based on a two phases approach. First phase is a preprocessing work where the geographical information is analyzed and clustered to best fit the needs of the optimization approach used to solve the VRP problem. The computation time of the minimum cost paths between the transport operation location is reduced. Furthermore, the GIS data clustering can be also used to reduce the search space of feasible solutions at the optimization phase. In the second phase, transportation resources are allocated and the corresponding routes are calculated considering the shortest path structures obtained at the first phase. We relay on two approaches for modelling and solving the VRP: Constraint Programming and techniques where simulation and search are combined.

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