Intelligent Platform for Sustainable Routing

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Abstract: Enterprises in the road transportation sector have to face several difficult challenges. Namely, they have to design distribution strategies and policies which combine economic efficiency with sustainability criteria. This issue is critical, especially for small and medium enterprises (SME), since they hardly have the economic and human resources necessary to implement and manage the complex mathematical methods associated with routing optimization -i.e. metaheuristics, mathematical programming methods, and so on. This paper presents a software platform that integrates different applications aimed to the support decision making in the efficient and sustainable fleet management.

Keywords: Transport Logistics, VRP, Optimization, and Simulation.

1. Introduction

Road transportation is the predominant way of transporting goods in Europe and also in other parts of the world. Direct costs associated with road transportation have experienced a significant increase since 2000, and more so during these last years due to the rise of oil price. Furthermore, road transportation has several indirect or external costs associated, which usually are easily observable –noise, pollution, accidents, etc.– but difficult to quantify. Noise due to road transportation in metropolitan areas constitute a serious challenge for the competitiveness of European industry: according to recent studies, external costs due to traffic jams could represent about 0.5% of the European GDP (Gross Domestic Product), a percentage which follows an increasing trend. Furthermore, taking into account the whole road transportation in Europe, a 0.51% of the GDP is due to noise and a 2% due to pollution. In addition to these easily observable costs, we could also add other costs such as the pollution costs due to the production and use of fossil fuel, among others.

Freight transport in metropolitan areas deserves special attention due to the high number of inefficiencies currently present. The fleet management problem in metropolitan areas is equivalent to the problem of 'last mile' in communications. It is relatively easy to carry the cable to the telephone in the neighborhood but is costly and expensive to carry this wire to each of the houses in the neighborhood.

The need for transportation services and infrastructures is considered to be an essential condition for the economic development of Europe (European Commission, 2001). In this sense, some studies have highlighted the existence of a significant correlation between available infrastructures and economic development. Thus, the transportation activity is strongly connected with the economic development and, moreover, it is an important source of externalities, which can slow down the expansion of a sustainable economy. Therefore, we can consider the following aspects associated with transportation:

- Transportation is an essential production factor in most economic activities. The geographic nature of transportation and the difficulties to warehouse some products make the transport planning a core activity (Bates, 1998).
- The quality of transportation systems has a great influence over the demand of goods. This quality depends, among other factors, on the time needed to perform the transportation activities. Also, considering quality factors might change the costs structure in transportation companies (Oum & Waters, 1998).
- It is often possible to find externalities and scale economies involving enormous divergences between the social marginal costs and the private marginal costs. This fact, together with the existence of external costs associated with transportation activities, justifies the necessity of technological improvements that contribute to a sustainable and efficient assignment of transportation resources.

The traditional vision of transportation as an economic sector (Economy of Transportation) shows some pitfalls when facing some of the challenges previously described. In this scenario, it becomes evident the necessity of developing new methods, models and systems to give support to the decision-making process so that optimal strategies can be chosen in road transportation. This necessity for optimizing the road transportation affects to both the public and the private sectors, and constitutes a major challenge for the EU. Concerning Spain, the concerns about criteria of sustainability in transportation are present in many of the structural policies of the Spanish Ministry of Transportation (Ministerio de Fomento, 2004-07) described in the *Plan Estratégico de Infraestructuras y Transporte* (PEIT) for the period 2005-2020.

The main purpose of this paper is to present the technological platform (Ramos et al., 2006), which has been developed by the research team for the optimization of road transportation problems. This platform is currently being commercialized by DLM Group (www.dlm-solutions.com).

The paper is structured as follows. Section 2 describes the fleet management platform. Section 3 illustrates the presented technology by means of a real application case. Some conclusion remarks are discussed at Section 4.

2. The ITSLogisim VRP platform ©

The purpose of the fleet management platform is the integration and application of methods and systems for routing optimisation that take into account economic and efficiency criteria for a sustainable road transportation.

The platform (see Figure 1) is based on a distributed architecture, since different technologies and tools must be integrated. The two modules are briefly described in the following subsections.

2.1 Geographical information System

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 georeferences to the position of each vehicle and to the position of the transport operations, as well as their characteristics, which depend on the VRP being solved.

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. The application Shortest Path Generator (SPG) has been developed to represent the geographical data in the most suitable way for the optimization problem. A more efficient data structure, based on a pre-clustering process, is obtained from the information provided by the cartography. SPG can thus represent the minimum cost paths among the relevant geographical nodes with an acceptable computational effort.

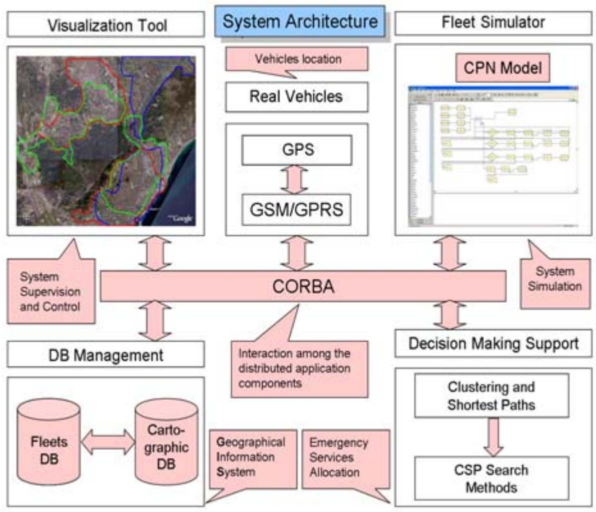

Figure 1. Distributed architecture of the ITSLogisim VRP platform

The clustering process is problem dependent. For example, a clustering process based on isochrones is applied for allocating emergency service resources in road accidents (Guimarans et Ramos 2007). In the application case described in Section 3, the clustering process is based on *centroid* calculations since customer locations are known for long periods and resource workload has to be balanced. Clustering approaches based on postal codes are currently under development in order to face pick and delivery distribution problems.

2.2 Decision making support

The Vehicle Routing Problem (VRP) is among the most popular research areas in combinatorial optimization. Since it was first defined by Dantzig and Ramser (1959), several variants of the basic problem have been proposed and studied. Several formulations and exact algorithms have been proposed to solve the VRP. However, for large instances the time required to solve them becomes absolutely prohibitive due to its NP-hardness.

The platform implements flexible, efficient and robust optimization algorithms able to deal with real problems, which means both the ability to tackle large instances and to represent real operational constraints. The characteristics of those algorithms can be explained in the following way: flexibility involves the quality of the algorithms to be adapted to real problems having stochastic or uncertain variables; efficiency is related to the easiness of the algorithms to obtain optimal or quasi-optimal solutions in reasonable computation times; and robustness is related to the simplicity of the algorithms structures.

The implemented VRP optimization scheme is based on a hybrid approach that combines metaheuristics, Constraint Programming (CP) and Lagrangean Relaxation methods (LR). Numerous heuristics and metaheuristics have been studied for different VRP variants. In most cases, these methods may solve larger instances but loosing optimality guarantees. This field has deserved special attention from the research community and has stimulated the emergence and the growth of several metaheuristics of general applicability. A recent overview of available methods for different VRP variants can be found in (Cordeau et al. 2007).

Compared with classical heuristics, such as route construction and improvement methods or two-phase approaches, metaheuristics are less likely to end trapped in a local optimum. Among metaheuristics, Variable Neighbourhood Search (VNS) was introduced for the first time in (Mladenovic and Hansen 1997). Interesting results have been obtained even applying the simplest VNS algorithm (Bräysy, 2003; Hasle and Kloster, 2007; Rousseau et al., 2002; Guimarans et Al. 2010).

The VNS metaheuristics has been implemented as the general framework where to embed CP and Lagrangean Relaxation LR approaches to the Capacitated Vehicle Routing Problem (CVRP). By using these two well-known paradigms within the VNS local search process, calculation time has been reduced with respect to classical VNS schemes, obtaining high quality solutions (Guimarans et Al. 2010). Furthermore, this hybrid scheme has the required flexibility and robustness to tackle real application problems (see Section 3).

A simplified scheme of the implemented VNS method is presented in Figure 2. At each iteration, a local minimum is reached departing from an initial solution. A diversification process (shaking) ensures that different regions from the search space are explored by changing the initial solution at each iteration.

As a first step for the algorithm, an initial feasible solution is found using CP and LR. CP is used to assign all customers to available resources fulfilling capacity constraints, while resulting routes are solved to optimality by means of LR.

The local search step implements the VND algorithm illustrated in Figure 3. The VND local search implements four different inter-routes classic moves (Savelsbergh, 1988):

- *Relocate*: moves a customer from one route to a different one.
- *Swapping*: exchanges two customers belonging to two different routes.
- *Chain*: swaps sections of two contiguous customers from two different routes.
- *Ejection chain*: swaps the end portions of two different routes.

Within the VND algorithm, an exhaustive exploration of the l^{th} neighborhood $N_l(x')$ of x' is performed. Departing from the solution x', the l^{th} move is applied and new solution's feasibility is checked using CP. Whenever it is proved feasible, LR is used to recalculate only modified routes. Since LR provides optimal routes, no intra-route moves are required.

Finally, the chosen VNS stopping criterion is based on the maximum number of iterations.

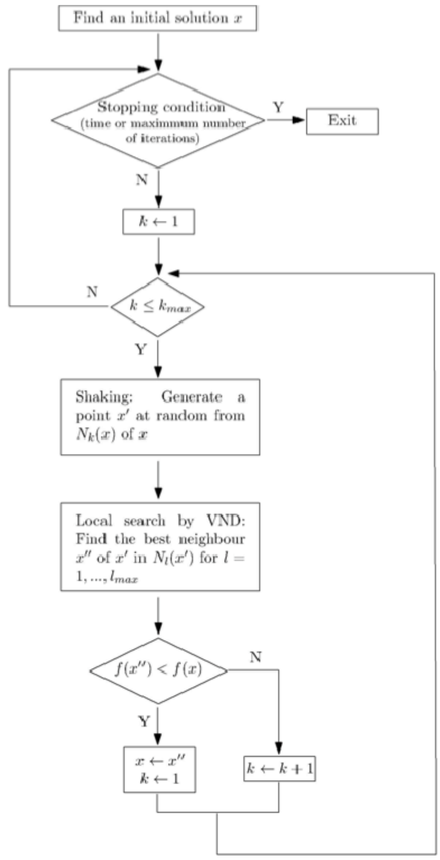

Figure 2. Variable Neighborhood Search (VNS)

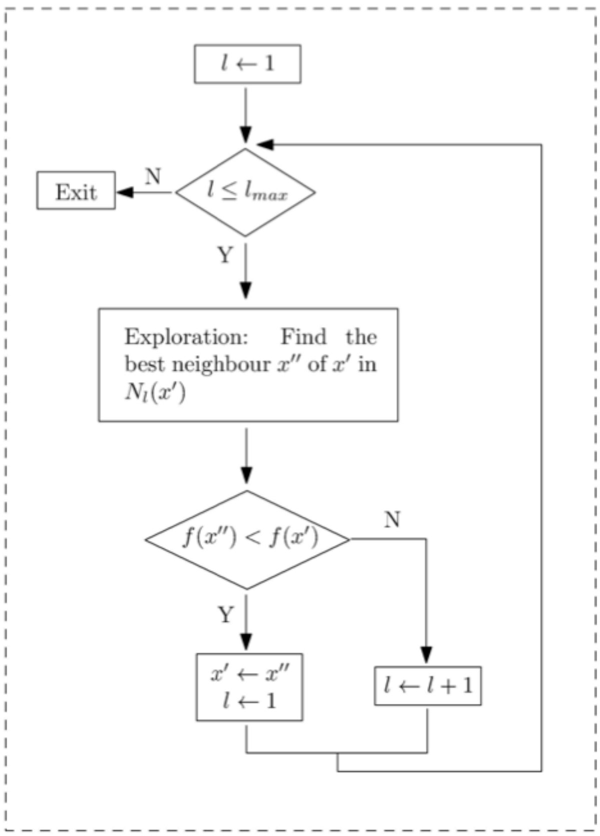

Figure 3. Variable Neighborhood Descent (VND)

As mentioned, the described hybrid algorithm embeds CP and LR within the VNS metaheuristics framework. In the proposed model, the CVRP has been divided into two subproblems, concerning customers' allocation and routing optimization separately. The first is aimed to assign customers to resources by fulfilling capacity limitations. The latter is used to solve each independent route to optimality, giving the best solution for a particular allocation. CP is used to find a feasible solution in terms of capacity, while LR solves routing problems.

Constraint Programming is a powerful paradigm for representing and solving a wide range of combinatorial problems. Problems are expressed in terms of three entities: variables, their corresponding domains and constraints relating them. The problems can then be solved using complete techniques such as depth-first search for satisfaction and branch and bound for optimization, or even tailored search methods for specific problems. (Rossi et al. 2006) presents a complete overview of CP modelling techniques, algorithms, tools and applications. Capacity constraints can significantly vary from one application case to others. The implemented scheme provides the required flexibility since only the capacity constraint model must be changed for tackling different application cases.

Lagrangean Relaxation is a well-known method to solve large-scale combinatorial optimization problems. For a recent review, see (Guignard 2003). LR exploits the structure of the problem, so it reduces considerably problem's complexity. Thus, the Lagrangean Problem needs less computational effort to be solved. However, it is often a major issue to find the optimal Lagrangean multipliers. The commonly used approach is the subgradient method. It guarantees convergence, but it is too slow to become a method of real practical interest.

In order to avoid this limitation, a tailored LR method is applied to calculate routes every time a partial solution is generated either during initialization, diversification or local search processes. The implemented LR-based method (Rosa *et Al.* 2010) improves the convergence on the optimal solution of the Subgradient Optimization by using a heuristic to obtain a feasible solution from a LR solution. If the optimal solution is not reached at a reasonable number of iterations, the proposed method is able to provide a feasible solution with a tight gap between the primal and the optimal cost. By using this LR implementation, the computation time is significantly reduced when compared to other routing post-optimization methods. So, the proposed LR approach provides optimal routes in very low times and, at the same time.

3. A real application case

The presented platform is currently being commercialized and several real applications are already implemented or under development. This section describes one of these real case applications. Because of confidentiality reasons, the company name cannot be given here and some details must be omitted.

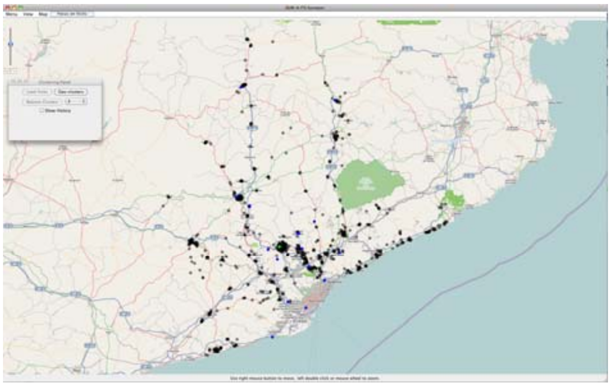

Figure 4. Customer location corresponding to Barcelona province (except for the urban and metropolitan area)

The distribution problem has more than 22.000 customer locations scattered all over Spain. The company has different distribution centres, strategically located. Customers must be visited on a weekly or fortnightly basis. Additionally, there exist different types of operations that can occur stochastically. Usually, the priority of these events is higher than the regular operations. Nevertheless, the company has good statistics modelling the non-deterministic operations.

Before adopting the presented platform, the company made all the routing decision processes based on the human expertise. That was a huge time-consuming process, with inefficiencies (basically, resource overestimation) due to the problem complexity. The company expectations were twofold: to reduce the workload expended in route construction and to improve the performance at the routes (fewer transport resources and more sustainable routes).

This problem falls into the large instance VRP category, and it is a big deal even for metaheuristics methods. Hence, a cluster-first/route-second strategy (Dondo *et Al.* 2005) is applied in order to split the problem into a set of subproblems that can be separately solved.

3.1 The clustering process

Two clustering phases are applied before solving the routing problem. Each distribution centre has its own resources, so this first stage clustering uses the distribution centre locations to assign customers. The clustering method uses customer distance to the associated depot maximizing the savings. The number of assigned customers is limited by the resource capacities of the distribution centre. The Figure 4 shows a cluster obtained at this phase. A typical cluster at this stage can range between 1000 and 3000 costumers. So, still a big deal for the optimization algorithm.

A second clustering process is applied then. At this second stage, other operational constraints, in addition to the capacity ones, are applied. The main objective is to minimize the time to serve the non-deterministic operations that cannot be considered during the routing phase due to their stochastic occurrence. The Figure 5 shows the resulting routing clusters. A routing cluster is a customer set that must be served by the same resources.

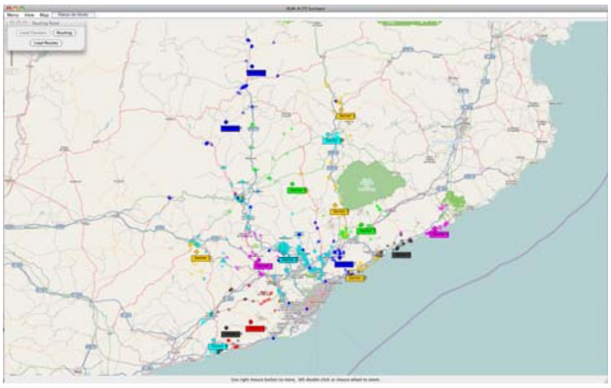

Figure 5. Clusters that are obtained by applying operational and capacity constraints of a resource.

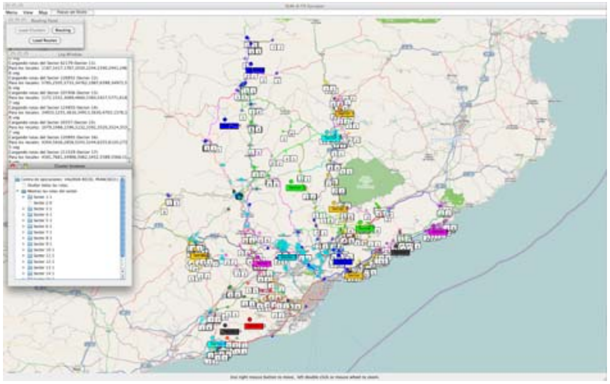

Figure 6. View of the routes calculated at the example cluster.

3.2 The routing process

The VRP optimization algorithm is applied to each routing cluster. A typical routing sector ranges from 75 to 100 customers depending on the geographical area, since the area has a strong impact over travelling times. In this application case, the resource capacity is expressed in terms of operation and travel time. The objective is to minimize the travel time, so the maximum number of customers can be served within a labour day.

Customers must be served regularly either weekly or fortnightly. Hence, the planning horizon for the regular operation is two weeks (10 working days). The optimization outputs are the daily routes that must be executed by each resource (see Figure 6 and Figure 7). However, non-deterministic operations can occur anytime, and usually they have higher priority than the regular ones. When these events occur, the planned route likely can no be executed. Nevertheless, the resource capacity to assume stochastic operations is ensured. The statistic models of these events were taken into account during the routing cluster building, so that the probability to exceed the resource capacity is minimized. In order to provide the better answer to the non-deterministic operations, the platform implements a re-planning module that re-builds the routes which are pending in the planned horizon. The objective here is to minimize the overtime hours (if they are required).

It is worthy to remark the flexibility of the optimization scheme. The operational constraints of this particular application case are far more complicated than the usual capacity problems (weight, volume, etc.). Nevertheless, a small effort, beyond the modelling cost itself, was necessary to adapt the generic CVRP algorithm (Guimarans *et Al.* 2010) to this application case.

4. Conclusions

The paper has presented a distributed platform that has been developed to assist in the design of pseudo-optimal routes in transportation logistics problems. Because of its modular and distributed structure, this technological platform can be easily adapted to deal with different VRP. Furthermore, the optimization scheme has been shown to be flexible enough in order to face different VRP real problems.

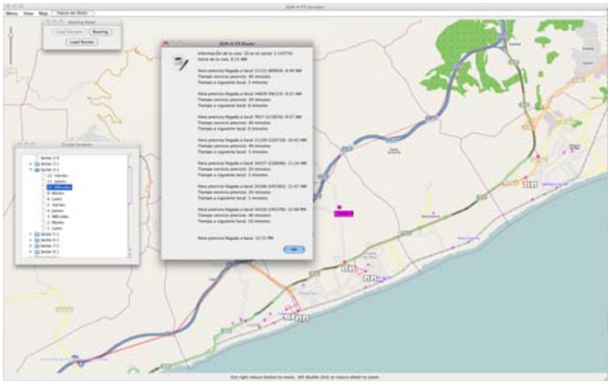

Figure 7. Detail of a route showing travel cost and operation times.

A real application case has been discussed. The company is currently evaluating the solutions provided by the optimization tool. Indeed, results are promising since the proposed routes consume fewer resources (idleness has been significantly reduced) and the performance dealing with the non-deterministic operations has been improved (worker overtime has been reduced). Furthermore, the obtained routes are more cost effective, in terms of time and expended fuel, than the current ones.

In the implemented optimization approach, the CVRP has been decomposed into two separated subproblems. The first one is aimed to assign customers to resources in terms of capacity, while the second is used to optimize corresponding routes. This approach allows reducing the computation time, since problems to be solved are far less complex than the original CVRP, although still NP-hard.

The proposed LR-based method permits to reduce calculation times due to its improved convergence with respect to the Subgradient Optimization classical algorithm. It also provides optimal routes. Computation times at the application real cases are in the order of milliseconds (Mac OS X, CPU-i7 4 cores, 4GB of memory). At the same time, the adopted CP approach has demonstrated to be efficient both for solving the capacity subproblem and for checking feasibility at runtime. Solving the routing problem for a distribution centre (with 1000 customers approx.) takes about 1’5 hours, while this process used to take several days when performed manually. It should be remarked that the provided execution times has been obtained with sequential implementation of the optimization scheme. A parallel implementation is being implemented to take advantage of the clustering based approach. The optimization scheme has also demonstrated its flexibility to be adapted to different real cases.

Several lines for future research are open. First, different VNS schemes are being studied, such as Variable Neighbourhood Decomposition Search, whose shaking process can be improved by embedding CP techniques. Second, heuristic methods are to be included into the neighbourhood exploration phase.

Acknowledgments

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