

Solving Multi-modal and Uni-modal Transportation Problems through TIMIPlan

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Abstract: The goal of this paper is to describe TIMIPlan, an application that solves the multi-modal and uni-modal transportation problems of one of the largest Spanish transportation companies. The first problem, related to multi-modal transportation, reflects the combination of at least two modes of transport in a single transport chain, without change of container for the goods. In this paper we describe a hybrid algorithm, combining Linear Programming and Automated Planning, to tackle the multi-modal transportation problem exploiting the benefits of both kinds of techniques. The second problem refers to a common uni-modal transportation problem: the delivering of goods from a central depot to consumers with time windows, and where only the road transport mode is used. This is the well-known Vehicle Routing Transportation Problem with Time Windows (VRTPTW). In this paper we describe an ant colony optimization approach used to solve the VRTPTW.

Keywords: Multi-modal transport, Linear programming, Automated Planning, VRTPTW, Ant Colony Optimization

1. INTRODUCTION

Nowadays, efficient transportation methods play a key role in transportation companies. Uni-modal transportation is one of the most important and successful applications of quantitative analysis to solve business problems dealing with the physical distribution of goods (Nanry and Wesley Barnes [2000]). In these problems, the purpose is to minimize the cost of shipping goods from one location to another using only one mode of transport, usually the road transport. In the case of international logistics companies, the use of multi-modal transportation, using a combination of at least two modes of movement of goods, such as road, rail, or sea, represents a good choice to reduce transportation cost (Macharis and Bontekoning [2004]).

In this paper we describe an application called TIMIPlan we have developed to solve successfully the multi-modal and uni-modal transportation problems of one of the largest Spanish transportation companies. The multi-modal problem deals with long distance transportation, while the uni-modal problem deals with short distance transportation. The particular multi-modal problem considered here fits into the multi-modal chain of container transportation services described in the literature (Crainic and Kim [2007]). This chain usually links the initial pick-up point to the final delivery point of the container, visiting in between different pick-up and delivery points. Transportation is provided by several carriers. The multi-modal planning component of TIMIPlan consists of two phases: in phase one, for each set of goods to be picked up

and delivered, the containers and trucks with minimum estimated cost to complete the service are selected. In this phase, several assignment models are constructed and solved as linear programming problems. In phase two, an Artificial Intelligence (AI) planner is used to select the best (least cost) plan to serve each service: from a first pick-up point to the last delivery point over the transportation route. The plan should fulfill a given set of constraints (temporal and regulatory), and will include the sequence of the transportation modes to be used (Flórez et al. [2011]). Although some of the application areas addressed in AI and Operations Research (OR) are very similar (e.g., planning, scheduling), the methods that are used to solve these problems are substantially different.

On the other hand, the uni-modal problem described here fits into the **Vehicle Routing Transportation Problem with Time Windows (VRTPTW)**, well-studied in the literature (Bräysy and Gendreau [2005]). The VRTPTW problem can be described as the problem of designing least cost routes from one depot to a set of geographically dispersed demand points. The routes must be designed in such a way that each demand point is visited only once by exactly one vehicle within a given time window. Additionally, all routes start and end at the depot, and the total demands of all points on one particular route must not exceed the capacity of the vehicle. In this case, we describe the **Multi-Objective Ant Colony Optimization (MOACO)** technique (López-Ibáñez and Stützle [2010]) used to solve the VRTPTW problem.

The remainder of this paper is organized as follows. Next section gives a brief summary of the transportation problem in its uni-modal and multi-modal versions, introducing some of the main approaches used to solve it. Section 3 describes the concrete multi-modal and uni-modal transport problems we deal with here. Section 4 presents the TIMI-Plan application. Section 5 includes experiments relative to the algorithms used in the multi-modal and uni-modal transport. Lastly, Section 6 presents the conclusions and further research.

2. RELATED WORK

There have been already many approaches that deal with the uni-modal transport problem (Nanry and Wesley Barnes [2000]). An overview of methods that approach the pickup and delivery problem and vehicle routing problem can be found in Desaulniers et al. [2000], Ropke and Pisinger [2006]. Ant colony systems (ACS) have been widely used to solve the transportation problem. An example is the algorithm MACS-VRPTW (Gambardella et al. [1999]). This algorithm is organized with a hierarchy of artificial ant colonies designed to optimize a multiple objective function using two different colonies: the first one minimizes the number of vehicles while the second one minimizes the traveled distance. In Montemanni et al. [2003], a new algorithm based on ACS is presented to solve a new class of problems in dynamic vehicle routing, where new requests are received as time progresses and must be dynamically incorporated into an evolving schedule. However, in contrast with these approaches, we deal with a real world problem with several differences to the classical VRPTW problem. These differences are detailed in Section 3.2.

In the multi-modal transport problem there has also been some work done, though none of these works solves the complete logistics problem, being centered in other problems associated with multi-modal transportation or in sub-problems that do not represent all the constraints considered here (Macharis and Bontekoning [2004]). In Catalani [2003], a statistical study is presented to improve the intermodal freight transport through Italy, by using the road-ship and road-train transports. In this study, only the main points of origin or destination are taken into account, so the study does not deal with the complete network complexity problem, as we do. In Qu and Chen [2008], the authors pose the multi-modal transport problem as a Multicriteria Decision Making Process (MCDM). They propose a hybrid MCDM by combining a Feed-forward Artificial Neuronal Network with a Fuzzy Analytic Hierarchy Process. The case study is a network in which nodes represent terminals, and edges represent different transportation modes (road, ship and train). The model can deal with several cost functions and constraints, but they only define six nodes, while our maps can have thousands of nodes.

3. PROBLEM DESCRIPTIONS

We define next the two problems for which we have generated the software tool.

3.1 Multi-Modal Transportation Problem

We define a multi-modal problem as the tuple $\langle G, F, C, R, B, S \rangle$ where G is the network graph, F , C , R and B are

the sets of trucks, containers, trains and ships respectively and S the services that should be fulfilled. The nodes in G represent the locations where the goods should be picked up or delivered. A service $s \in S$ specifies pickup and delivery operations, each one with a location and service time, that indicates the time at which the corresponding location is available for the pick-up or the time at which a delivery service should be performed. To complete a service only a container $c \in C$ is required, but it can be moved by using a combination of vehicles: trucks, trains and/or ships. Each truck $t \in F$ has information relative to the location and time at which it will be available and its corresponding driver's accumulated driving time. If a truck is used, it should travel to pick the container up, and either visit all locations of the transportation request (pick up and delivery locations), or transport it to the next transportation means (train station or port), where the rest of the plan might involve one or several other transportation vehicles. Trains and ships have a timetable specifying their movement actions and the load and unload actions can only be executed when they are in a station/port. The resulting plan should satisfy the given service times of the locations. For instance, if the truck and container arrive early, they have to wait at the location until it is available. If the truck and container arrive late, there will be a cost penalty.

In multi-modal transportation, several trucks are usually needed. For example, Figure 1 shows how, in order to complete the service, there are five available trucks, one container, two trains and two ships. The first truck with the container picks the shipment up from $Pick-Up_1$ and transports it to $Pick-Up_2$ using either road or train. If the train option is selected, another truck will be necessary to transport the container to $Pick-Up_2$. Also, there are two other decision points related to the use of $Ship_1$ and $Train_2$. The use of $Ship_2$ and $Truck_4$ is mandatory for reaching the $Pick-Up_3$ point.

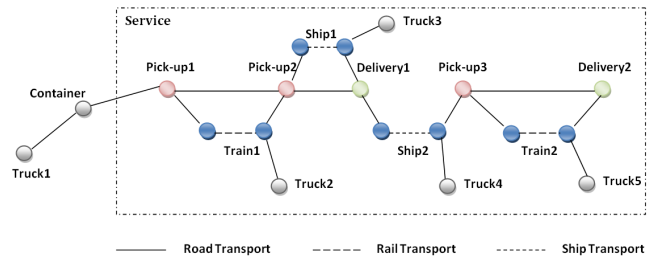


Fig. 1. Example of multi-modal transportation graph.

Thus, there are several kinds of resources, each one with different kinds of costs (e.g., moving the truck empty is different from moving it loaded), different routes (either single mode routes, as all road, or multi-modal routes, as combining trucks with barge and/or rail), and with temporal and resource constraints (drivers have constraints on number of continuous driving hours, for instance). Several constraints have not been included in the previous description of the problem, due to the difficulty of formalizing them or because they depend on information that is not available in the system. For example, there are soft goals related to the places where the drivers prefer to stop or to the client's preferences about vehicles and/or containers

used to transport their goods. Also, human planners have expert knowledge about the probabilities of new services arising in each zone. They use that knowledge to reserve trucks or containers in these zones or make movements that prepare all resources for future unknown services. Given that it is impossible to predict all potential soft goals to be taken into account when planning, we use a mixed-initiative approach to help the user taking into account those constraints that cannot be easily handled by TIMIPlan.

The planner is executed every day. A daily problem has approximately 600 locations (summing up all pick-up and delivery locations, as well as initial positions of trucks, containers, ships, and trains), 175,000 edges among those locations, 300 trucks, 300 containers, 300 services, 50 train segments and 150 ship segments. The company imposes a time limit of 2 hours for computing the daily plan.

3.2 Uni-Modal Transportation Problem

We define the particular uni-modal transportation problem we consider here as the tuple $\langle G, V, S, d \rangle$ where G is the network graph, V the set of capacity-bounded vehicles, d the depot, and S the services, composed of a demand and a time window. The goal is to find the less number of routes as possible, starting and ending in the depot d . The primary objective is minimizing the number of vehicles used to fulfill the maximum number of services $s \in S$, within the time windows imposed for each service and without exceeding the capacity of the vehicles. The secondary objective function is minimizing the total cost. The total cost is computed taking into account the cost per kilometer of each vehicle and the distance traveled, and the waiting cost computed for each service when a vehicle arrives before the beginning of the time window. Our particular uni-modal problem has several differences with respect to the classical VRPTW problem:

- (1) In our problem, a limited number of vehicles, $|V|$, is given to completely fulfill all the services $s \in S$. The classical VRPTW problem assumes that the number of vehicles is unlimited, and the objective is to obtain a solution that minimizes the number of vehicles. In the real world problem we deal with here, this assumption is unrealistic.
- (2) Each vehicle has its own per kilometer and waiting costs. In the classical VRPTW problem it is assumed that all the vehicles have the same cost per kilometer, and the waiting cost is not considered.
- (3) The same vehicle can perform several routes during its workday, i.e. the vehicle comes back to the initial depot at the end of its first route, it is loaded again, it starts a new route, and so on.

The uni-modal planner is also executed daily. In this case, the biggest daily problem has approximately 18 vehicles and around 140 services.

4. TIMIPLAN

TIMIPlan is able to solve both multi-modal and uni-modal logistics problems. It is composed of a set of modules as shown in Figure 2. The input is the list of services to accomplish and the list of available resources (initial locations of each resource, costs, constraints, ...), both

in XML format. The output is a plan. This plan can be graphically inspected on a map which includes points where the actions are performed and the routes followed by the vehicles. The Web access component performs different queries to Web portals like Google Maps, postal codes services or traffic information. The main module fuses all the gathered data to generate the problem description and delegates the work to the planning and monitoring modules. Once TIMIPlan creates the problem description, it is passed to the multi-modal or the uni-modal planner (depending on whether the problem to be solved is multi-modal or uni-modal). The Monitoring component in the multi-modal case allows TIMIPlan to detect deviations from the original plan, or new services to be planned for, that arise everyday, and triggers replanning (as, for instance, when a truck is damaged) when necessary. In the uni-modal case, the Monitoring module allows users to supervise the compliance of the plans, detecting delays and damaged vehicles, and to notify these situations to the users.

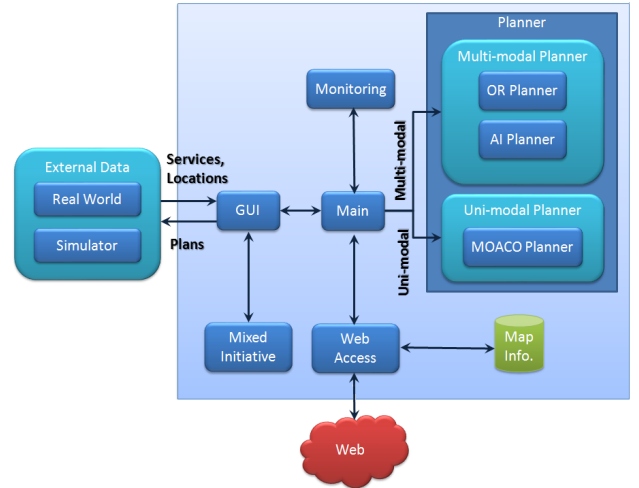


Fig. 2. TIMIPlan architecture.

For a full integration with the company's information systems, TIMIPlan has to support two modes of operation: offline and online. The offline mode runs everyday to generate the next day's planning. In the online mode, the system monitors the position of each resource, the execution of actions and the replanning when necessary. The system also incorporates a simulator that allows users to analyze potential plan alternatives. The mixed initiative module allows users to interact with TIMIPlan in order to: include extra information in the problem; plan to consider the constraints and goals that cannot be formalized explicitly; or solve unexpected failures.

4.1 Planning Module

In this section, we describe the planning techniques we have used to solve both problems.

Multi-modal Planner

We decompose the planning process of multi-modal transportation problems into two phases. First, we compute the assignment of trucks and containers to services taking into account the initial positions of the trucks and

containers, using a Linear Programming (LP) approach. Then, our approach sequentially solves the problem, using three different steps for each service. In step one, the container and truck/s with minimum cost estimated to complete the service are selected. In step two, a planning module is used to select the *best* path from a first pick-up point to the last delivery point over the transportation route. In this case, *best* means that the path fulfills the given set of constraints, including the sequence of the transportation modes used (where several trains and/or ships can be used) with the minimum cost. This two-step approach balances the total cost obtained and the time required to compute the plan. The high level algorithm has been depicted in Table 1. The network graph is the graph defined by the locations (pick-up and delivery nodes, positions of trucks, containers, train stations and ports) and edges (roads, rails and ship lines). In step three, we update the assignment of trucks and containers to services taking into account the final position of the trucks and containers used to complete the last planned service. In the third step, we use the same LP approach again.

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Multi-modal(G, F, C, R, B, S): plan
;; Inputs: the graph (G), the set of trucks (F), containers (C), trains (R), ships
;; (B) and services (S)
plan = ∅
;; Compute the initial assignment of trucks and containers to services (A)
A = solveAssignmentProblem(G, F, C, R, B, S)
For each s ∈ S
    ;; Select the truck/s and container to complete the service
    selectedTrucks, selectedContainer = getServiceAssignment(A, s)
    ;; Plan the service with the truck/s and container selected. Select the best
    ;; transportation modes
    plan = ∪ {solvePlanningProblem(selectedTrucks,
    selectedContainer, R, B, s)}
    ;; Updates assignment with the new cost of selectedTrucks and
    ;; selectedContainer
    A = updateAssignmentProblem(G, F, C, R, B, S)
Return plan

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Table 1. Top level algorithm of multi-modal planner.

Assignment Problem In the classical assignment problem, the goal is to find an optimal (minimum cost) assignment of resources to tasks taking into account the constraints, and ensuring that all tasks are completed. In our case, given the size of the whole assignment problem, we decompose it into three subproblems. In the first subproblem, we solve the assignment of empty containers to trucks. The cost of a truck-container assignment is estimated taking into account the distance between them, the time at which they will be available and the transportation cost of each truck. In the second subproblem, we solve the assignment of trucks with containers to services, using the assignments computed in the previous phase. These operations involve the provision of an empty truck and container to the service. The truck and container are used in the subsequent transportation until they arrive to the last delivery point in the service or until they arrive to a multi-modal node in the transportation route. To estimate the assignment cost, we consider the position and time of both the service and the truck with container. In multi-modal transportation, additional trucks are needed in order to complete a service. These trucks pick-up the containers from the destination station/port and transport it to complete the service, or

until they arrive to the next multi-modal node. So in the third assignment subproblem, the method selects the best truck to pick-up the container from the destination station/port and continue the transportation route. It takes into account again the previous assignments.

Planning Problem One of the inputs of the planning process is the list of truck/s and container selected by the assignment process for each service. A planning problem is built for each service and the planner must select the best transportation modes to complete it. Moreover, the planner must schedule each pick-up and delivery according to the constraints. First, it selects the trains and ships that can potentially be used to complete the transportation route. Then, the planning problem is constructed taking into account the trains, ships and the truck/s and container selected to complete the transportation route. In our work, we use the SAYPHI planner (La Rosa et al. [2007]) and we use A* as the search algorithm.

Uni-modal Planner

Multi-criteria optimization problems are characterized by the fact that several objectives have to be simultaneously optimized. In this paper, we use the Multiobjective Ant Colony System (MOACS) (Gambardella et al. [1999]) algorithm, based on MOACO approaches. MOACS algorithm uses two different ant colonies to minimize two different objective functions. The first colony minimizes the number of vehicles, while the second colony minimizes the total traveling time. In the original MOACS algorithm, the first objective function takes precedence over the second one. In this paper, we propose three modifications to the original MOACS algorithms to work with the uni-modal problem we deal with here.

- (1) First, we consider two different objective functions: to minimize the number of vehicles, O_1 , and to minimize the total cost of the solution computed as $O_2 = \sum_i^n w(v_i) + c(v_i)d(v_i)$, where n is the total number of vehicles used in the proposed solution, $w(v_i)$ represents the total waiting cost of the vehicle v_i computed at each service when it arrives before the beginning of the time window, $c(v_i)$ is the cost per kilometer of the vehicle v_i , and $d(v_i)$ is the distance in kilometers traveled by the vehicle v_i .
- (2) Second, TIMIPan allows the users to select the objective that takes precedence over the other one. For the multiple objective algorithm described here, we consider the weighted objective function $O = p_1O_1 + p_2O_2$, where the user selects if $p_1 > p_2$ or $p_1 < p_2$.
- (3) Third, we have modified the original MOACS algorithm to allow the same vehicle to be used several times in the same planning process. If a vehicle arrives to the depot, it may be re-selected to start a new route, but taking into account the time at which the vehicle completed the previous route.

4.2 Mixed Initiative

TIMIPan implements a fully planning process that allows the user, once the services are completed and the available resources are provided, to automatically obtain a complete plan. That plan takes into account most of the

constraints, but not all, because some cannot be represented or efficiently handled by the system. For example, drivers prefer services near home or prefer to work only on week days. In addition, several failures or changes may occur once the services are planned, which in the real world are fixed by humans in real time through phone calls. Finally, human experts are usually suspicious of tools that provide solutions which cannot be changed, regardless of how sophisticated or intelligent the tool is. Thus, a mixed-initiative component has been implemented to allow the human planners to modify the plans provided by TIMIPlan, according to their suggestions made during the project. Currently, in the inter-modal case, they can change means of transport, such as trucks, containers or ships, and change the order of pickup and delivery operations. Instead, in the uni-modal case, they can change a service or a vehicle from a planned route to another route. All these changes are performed through the GUI, that also propagates the effects of these changes: whether the plan is still valid (it does not violate any constraint) and what its new cost is.

4.3 Monitoring and Replanning

The monitoring component checks whether the execution of the plan is deviating from the expected and triggers replanning if needed. Given that we are dealing with a real-time system, with a large number of resources involved, it is not possible to replan from scratch. So, our replanning component consists on adapting the existing plan to the new state, aiming to perturb the original plan as little as possible (also known as *plan repair* (Fox et al. [2006])). In the multi-modal case, we consider three kinds of situations that may occur during the monitoring process: damaged trucks (providing new trucks to complete the service), new services (planning the new service), and traffic jams (propagating delays and recomputing costs). In the uni-modal case, we consider two different situations: traffic jams (acting in a similar manner as in the multi-modal case), and unfulfilled services (these services are transferred to the planning process of the next workday). If some other unexpected situation arises during the monitoring process, this module delegates on the mixed-initiative component, allowing the human experts to solve it.

5. EMPIRICAL EVALUATION OF TIMIPLAN

This section presents the evaluation of TIMIPlan. To evaluate the planning module, we use a set of representative problems, based on the real data gathered by the company. For the multi-modal case, the problems were generated using ship routes and pick-up and delivery points gathered from real problems. There has been a positive qualitative evaluation from users. Two versions of the multi-modal algorithm are used to solve problems of different sizes. Both versions differ on how they perform the first step of the algorithm: the assignment of truck/s and container to services. The first algorithm was explained in Section 4 (we will call it TIMIPlan Multi-modal (LP)). In this algorithm, LP techniques are used to solve the assignment of truck/s and containers to services. In the second version of the algorithm, a greedy approach is used to select at each step the container and truck/s with least estimated cost for

each service (TIMIPlan Multi-modal (Greedy)). In this case, no cost matrix is built as in the TIMIPlan Multi-modal (LP) algorithm, selecting greedily for each service the truck and container with the least estimated cost. We define ten types of problems in ascending order of size. Each problem has a linear increase in the number of services (between 75 and 300), nodes (between 150 and 600), trucks (between 75 and 300), containers (between 75 and 300), ships segments (between 60 and 150) and train segments (between 5 and 50). For each problem size, ten different problems are solved in order to obtain representative mean values and standard deviations. The experiments were conducted on a 2,4 GHz quadcore processor with 4 GB RAM, running Linux.

In order to analyze the sensitivity of both solutions to the costs defined by the company, we studied three different cost configurations, ordered in decreasing order of cost (costs of configuration 1 are higher than those of configuration 3). Figure 3 shows the comparison of quality (cost) of solutions of the same problems solved previously using the three cost configurations. In Figure 3, the costs are expressed in millions of euros. In this case, the solid red line labeled as *TIMIPlan multi-modal (LP)* shows the mean costs and standard deviations obtained by the TIMIPlan multi-modal algorithm when it uses LP, while the dashed blue line shows *TIMIPlan multi-modal (Greedy)* behavior. In all cases, the mean cost obtained by *TIMIPlan multi-modal (LP)* is less than the cost obtained by the greedy approach.

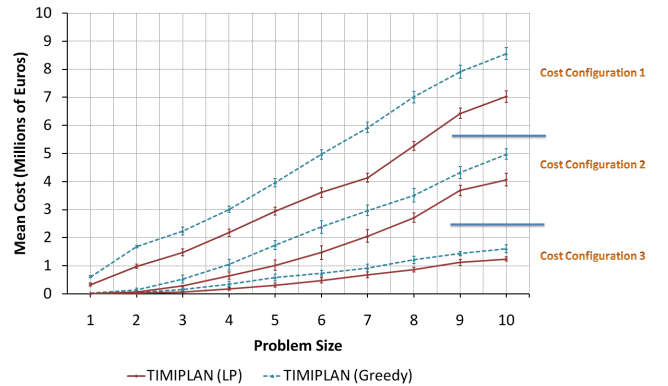


Fig. 3. Mean costs (in million euros) and standard deviations for the three proposed cost configurations.

In the case of the uni-modal task, the problems were again generated using services and vehicles configurations gathered from real problems. Table 2 shows the time (in seconds) to solve problems of different sizes using the TIMIPlan uni-modal algorithm proposed here, compared with other multi-objective ant colony optimization algorithm, M3AS, and simulated annealing. The TIMIPlan uni-modal algorithm performs better than the other algorithms in most of problems.

Table 3 shows the results of the TIMIPlan uni-modal algorithm for different number of services using different optimization criteria, where the problems have been generated using services and vehicles configurations gathered from real problems. The column labeled as *Optimization* represents the objective that takes preference over the other one (e.g. $O_1 > O_2$ means minimizing the number of

Problem #	Services	TIMIPlan Uni-Modal	M3AS	Simulated Annealing
1	10	0.44	0.43	1.74
2	40	1.74	1.86	5.89
3	100	44.54	45.90	50.96
4	150	171.72	172.73	169.23

Table 2. Time in seconds for solving problems of different sizes by different algorithms.

vehicles takes preferences over minimizing the total cost). The last two columns show the number of vehicles used to fulfill the services and the total cost. The optimization criterion $O_1 > O_2$ yields less number of vehicles to fulfill the services than when using $O_1 < O_2$.

Problem #	Services	Optimization	Vehicles	Total Cost
1	5	$O_1 > O_2$	1	99.58
		$O_1 < O_2$	2	85.54
2	50	$O_1 > O_2$	4	975.82
		$O_1 < O_2$	6	864.45
3	100	$O_1 > O_2$	9	1817.76
		$O_1 < O_2$	12	1512.96
4	140	$O_1 > O_2$	13	2674.52
		$O_1 < O_2$	15	2412.96

Table 3. Number of vehicles and total cost for different number of services.

6. CONCLUSIONS

In this paper, we have introduced TIMIPlan, a tool that successfully solves the particular multi-modal and uni-modal transportation problems of a big Spanish company. Multi-modal transportation usually involves the combination of a large number of resources, together with temporal constraints, resource consumption, cost functions, etc. Clearly the bottleneck in this problem is the combinatorial explosion which makes obtaining optimal solutions impossible in the time limit established by the company using only classical planning or only OR techniques. Instead, we decompose the problem into two different subproblems combining the use of LP and automated planning. This novel way of combining linear programming and planning has allowed us to balance the total cost (quality) obtained, the time required to compute a solution and the time to model the different optimization problems. In the case of the uni-modal transportation problem, we have introduced several modifications to the original MOACS algorithm to work with the real problem we deal with here. The experiments show that the modified MOACS algorithm successfully solves the uni-modal transportation problems of the company using different optimization criteria.

In order to finally deploy TIMIPlan we have to preprocess the databases (or include some kind of robust input parsing in order to remove the possible errors), and setting up GPS on both trucks and containers for monitoring and replanning. As future work, we consider combining LP and automated planning in a different way to find better solutions (lower cost) in less time to solve the multi-modal problem. In the uni-modal case, we forecast the use of different algorithms based on heuristic search to solve the problem.

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