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A EVOLUTIONARY ALGORITHM FOR DYNAMICALLY OPTIMISATION OF DRAYAGE OPERATIONS

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ABSTRACT— Proper planning of drayage operations is fundamental in the quest for the economic viability of intermodal freight transport. The work we present here is a dynamic optimization model which uses real-time knowledge of the fleet's position, permanently enabling the planner to reallocate tasks as the problem conditions change. Stochastic trip times are considered, both in the completion of each task and between tasks

Key Words: Drayage, Evolutionary algorithm

1. INTRODUCTION

Road transport has been and continues to be prevalent for the on land movement of freight. However, increasing road congestion and the necessity to find more sustainable means of transport has determined different governments to promote inter-modality as an alternative. For inter-modality to become viable for trips shorter than 700 km a cost reduction is necessary. Final road trips (drayage) represent 40% of the intermodal transport costs. It is possible to overcome this disadvantage and make intermodal transport more competitive through proper planning of the drayage operation.

Traditionally, optimization efforts focused on drayage operations concentrate on improving the cost and quality of service through the collaboration between drayage companies. Along this line, Morlok and Spasovic (1994) develop an integer programming model to plan truck and container movements in a centralised manner. They contemplate different payment options for drayage services and conclude that centralised management of drayage operations would result in savings between 43% and 63%, as well as an improvement in quality of service.

Following the path opened by De Meulemeester et al (1997) and Bodin et al (2000), the number of references on centralised drayage management has increased significantly over the last years, but most of them consider the problem only from a static and deterministic perspective. The main objective is normally the assignment of transportation tasks to the different vehicles, often with the presence of time windows (Wang and Regan, 2002). The first part of the work by Cheung and Hang (2003) develops a deterministic model with time windows, which is then solved by means of the discretization of each task's start and end time, and by incorporating the concept of dummy tasks for the beginning and the end of the vehicle's day. Ileri et al (2006) cover a large number of task types, both simple and combined, as well as the costs involved in drayage operations, and solve the problem with a column generation method. Smilovik (2006) and Francis et al (2007) incorporate flexible tasks where only the origin or the destination is precisely known.

Many works also include randomness in the generation of tasks (Bent and Van Hentenryck, 2004; Bertsimas, 1992; Gendreau et al, 1995) or dynamism in their assignment (Bent and Van Hentenryck, 2004; Psaraftis, 1995; Wang et al, 2007). However, it is hard to find randomness in trip times (Laporte et al, 1992), which is appropriate when the intermodal terminal requiring drayage operations is close to a large urban centre. Cheung and Hang (2003) and Cheung et al (2005) do consider the dynamic and stochastic characteristics of the drayage problem and solve it with a rolling window heuristic, but this randomness only affects the duration of the task, and not the displacement time between different tasks.

The work we present here considers random trip times both in the completion of each task and between tasks. It also incorporates real-time knowledge of the vehicles' position, which permanently enables the planner to reassign the tasks in case the problem conditions change. Section 3 generalizes the drayage problem as an Multi-Resource Routing Problem with flexible tasks. Section 4 describes the solution methodology for the dynamic and stochastic drayage problem, and section 5 applies this methodology to series of random test cases and summarizes the results. Section 6 summarizes the main conclusions of the work.

2. DRAYAGE PROBLEM DESCRIPTION

The drayage operation can be modeled as a Multi-Resource Routing Problem with Flexible Tasks (MRRP-FT) (Smilowitz, 2006). In a MRRP-FT multiple resources have to be used to complete a series of tasks. The MRRP-FT is defined as follows:

GIVEN: A set of tasks (both well defined and flexible) that require the use of some resources, with certain service times for each resource and time windows; a fleet of each resource type; operating hours at all locations; and a network with stochastic travel times.

FIND: A set of routes for each resource type that satisfies all the tasks while meeting an objective function (minimize operation costs) and observing operating rules for both tasks and resources.

The region where the drayage operations are performed is represented by a graph $G = (N, A)$. The nodes $i \in N$ represent the different facilities of interest for the problem: terminals, depots, loading/unloading points. To each of these nodes is associated a time to attach/detach the container to/from the vehicle, τ_i. Between each pair of nodes $i, j \in N$ there is an arc (i,j) characterized by the transit time τ_{ij}, not known in advance. The transit time has a discrete distribution associated, TT if known.

Every day a series of drayage tasks T must be completed, and the failure to do so implies a given subcontracting cost. The drayage tasks can be classified in two groups: well-defined tasks, T_w, and flexible tasks, T_f. Each $t \in T$ has a time window $[a_t^{ini}, b_t^{ini}]$ associated. This window limits the time period in which the task has to be completed.

Well-defined tasks represent movements between terminals and customers or vice versa, being both, origin $o_t \in N$ and destination $d_t \in N$ of the movement known. Time windows for well-defined tasks can be flexible, as shown in Figure 1: if the task represents the pickup of a container in the terminal, this task can never start before the train or vessel arrival, on the other hand, if the drayage driver is late then the task can still be completed although it will be penalized. In this last example, a given amount will have to be paid for the time the container remains waiting at the terminal. In a similar manner, if the task represents the delivery of a container to the terminal and it is completed before the allocated time, the container will also be subject to a waiting cost. This cost has been considered proportional to the waiting time.

Flexible tasks represent the movement of empty containers between customers and the depot. Delivery or collection movements of an empty container can take place between a customer and the depot, but also between customers under certain circumstances. For example, from a customer who has requested the collection of an empty container directly to another who has requested the delivery of an empty container, given that their time windows overlap. Therefore, for flexible tasks only the origin or destination is known a priori, and therefore multiple scenarios, denoted as R_t, are possible. The set of all movements, well-defined tasks and different scenarios generated by possible flexible tasks, is represented by M.

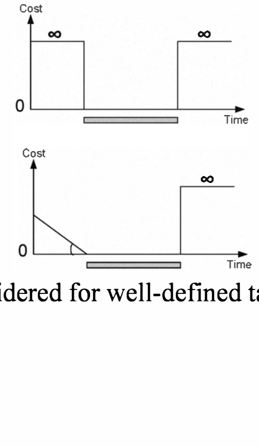

Figure 1: Types of time windows considered for well-defined tasks: hard (above) and flexible (below).

In order to perform all the tasks requested a set of resources is available: containers, vehicles and drivers. Containers are linked to the movement of the tasks with no additional restrictions. Driver-vehicle pairs are considered and represented by V. Each pair is characterised by a location where the working day starts and ends. The different drivers have a time window for the start of their working day $[a_v^{ini}, b_v^{ini}]$ and cannot work longer than MAX_v hours a day. In addition, driver-vehicle pairs have different costs per unit of time depending on vehicle stopping or moving.

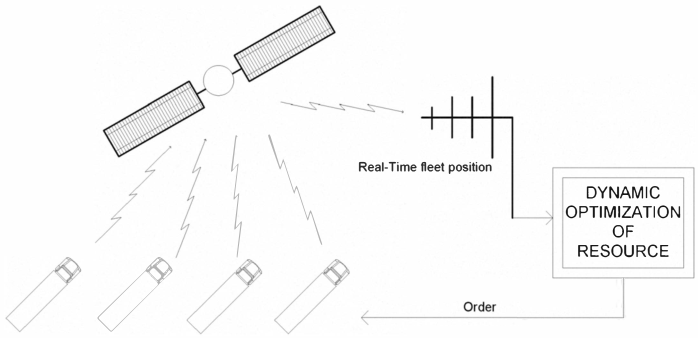

Figure 2: Use of real-time information.

In order to enrich the model with the dynamic condition, a geographic positioning system by satellite (GPS, Galileo, Glonass) is considered in order to provide real time information about the position of each vehicle. This data is used to improve the solution dynamically. Figure 2 shows a scheme of the functioning of the dynamic part of the system considered.

3. GENETIC ALGORITHM FOR STOCHASTIC TRANSIT TIME DRAYAGE PROBLEM

The static drayage problem is a NP hard problem extremely difficult to solve analytically. Exact solutions have been found for small problems, but computation time is high. The stochastic problem appears undoubtedly unsolvable analytically, even more so if flexible tasks are incorporated. Furthermore, the use of the real time information about the geographic position of the vehicles requires a high-speed procedure to find the solutions. An evolutionary algorithm has been used to solve the problem.

```
Genetic Algorithm
population = InitPopulation
for i=1:max_iter
    fitness = Evaluation (population);
    parents = SelectionTOP;
    child1 = GeneticCross(parents);
    child2 = Mutate (parents);
    population=population+child1+child2;
    dead=SelectionBOTTOM(population);
    population = population – dead;
    population=PopuGeneration
end
```

The chromosome which represents each solution is as shown in Wang et al (2007). In this representation, each chromosome is composed of some genes and each gene represents a task to complete. Each task is associated to a fixed gene. This gene is characterized by four features, first being the vehicle to which the task is associated, and is used to identify the order in which each vehicle completes the tasks. For example, in the table 1 the routes represented by the chromosome would be: vehicle 1, task1→ task2→ task4; and vehicle 2, task3→ task6→task5.

Table 1: Example of chromosome

1	2	3	4	5	6
1.123	1.673	2.234	1.942	2.440	2.294

The parameters of the genetic algorithm were tested with a sample of problems, and no clear tendency was observed in its performance. The population size was finally set to 100 individuals, 99 of which were initially generated at random and the last one by an insertion heuristic, which also provided the base for comparison of the effectiveness of the algorithm. In each generation, 4 are selected out of the 10 best individuals, and they are then allowed to cross and mutate with probabilities of 0.9 and 0.1 respectively. 4 out of the 10 worst individuals are then eliminated from the resulting population. The repetition of individuals is allowed in the population, which speeds up the performance of the algorithm, and when the average fitness of the population is only 10% worse than the best individual the population is regenerated randomly except only for that best individual.

The crossover operator switches the genes of two parents between two tasks which are selected randomly. The mutation operator selects randomly a gene of the parent individual and changes its first digit to another possibility.

The fitness of each individual represents the total costs of the resulting routes. The costs contemplated in each route are:

- Fixed cost per vehicle
- Distance cost
- Waiting cost of containers at the terminals due to early arrival or late collection
- Cost of task loss, assimilated to the subcontracting cost of that task to an external company

However, trip times are stochastic, so the fitness needs to be calculated as an estimation of the expected costs. An iterative algorithm was developed to complete that estimation, calculating the probability of reaching the next link of the route at a given time and the resulting costs involved. If the arrival time of the vehicle to the beginning of a given task is prior to the opening of its time window, the vehicle will wait, or else incur in a proportional cost. On the other hand, if the arrival is posterior to the closure of the time window, there is a higher penalty due to the waiting cost at the terminal or to the possible task loss (because of the departure of the train or vessel). If two tasks on the same route are both flexible and complementary, they will be combined and completed at the same time, thus avoiding the return to the depot.

With the real time information about the position of the vehicles, the input data to the algorithm will be dynamically updated and used to find the best routes depending on the current circumstances. This update can be done:

- Every a fixed time, for example 15 min.
- When a task is finished
- When a car position is diverted of its expected position.

4. TEST PROBLEM AND RESULT

In order to test the performance of the algorithm for problems of different size and characteristics, we built a set of random drayage problems using the problem generator (see Table 2).

Table 2: Problem set

Problem code	Task number	No of well-defined tasks	No of flexible tasks	Fleet size
A1	20	0	20	5
A2		5	15	5
A3		10	10	5
A4		15	5	5
A5		20	0	5
B1	30	0	30	7
B2		5	25	7
B3		10	20	7
B4		15	15	7
B5		20	10	7

B6		25	5	7
B7		30	0	7
C1	40	0	40	9
C2		10	30	9
C3		20	20	9
C4		30	10	9
C5		40	0	9

The generator of problem randomly distributes the customers, the intermodal terminal and the depot in a 100x100 area. The well-defined tasks consist, with equal probability, either of pickup or delivery of containers at the terminal, and flexible tasks will imply either collection or delivery of empty containers at the customers, also with equal probability.

Time windows for well-defined tasks range from 30 min. to 4 h. with a uniform stochastic distribution, and their start time is fixed randomly in the day. Time windows for flexible tasks will be open from the beginning of the day until the specified time for empty container deliveries and from the specified time until the end of the day for empty container collections. Those specified times are also generated randomly with a uniform distribution.

To simplify calculations, the time horizon is discretised in 5 minute intervals. Finally, to simulate in real time the position of each vehicle, a speed uniformly distributed between 45 and 55 km/h is calculated for each 5-minute period.

For each random problem, we determined the improvement of the genetic algorithm with respect to the insertion heuristic in the first iteration (see Table 3, column 2), the average improvement of the estimated cost for the best solution in iteration i+1 with respect to the simulated cost on iteration i (column 4), and the estimated cost reduction between the first and last iteration of the genetic algorithm (column 5).

Table 3: Results obtained for the random problem set

Problem code	Genetic vs. Insertion Improvement (%)	No of iterations	Average improvement of the GA (%)	Dynamic Improvement (%)
A1	12.7	6	2.19	31.88
A2	0.8	7	1.47	16.48
A3	0	8	0.28	16.08
A4	2.88	11	1.41	31.16
A5	9.6	14	3.46	31.11
B1	3.61	7	1.21	22.75
B2	4.36	9	1.27	39.41
B3	2.26	11	1.04	30.69
B4	4.04	9	1.43	23.04
B5	0	12	0.21	32.91
B6	1.36	13	1.22	30.19
B7	7.74	16	1.45	38.32
C1	1.66	7	0.68	12.87
C2	0.17	9	0.82	16.34
C3	1.42	13	1.85	25.13
C4	4.84	17	2.39	37.34
C5	9.83	18	2.05	33.42

5. CONCLUSION

We have shown in this paper the importance of the exact knowledge of real-time vehicle locations in a drayage fleet, through the use of a satellite positioning system. This knowledge, together with an optimization algorithm based on metaheuristics, enables real-time management of the fleet in a changing environment, which reduces operation costs by as much as 30%. These results are especially valuable for intermodal operations in congested metropolitan areas, where travel times are stochastic due to congestion. Besides, given that we modeled the problem as a MRRP with flexible tasks, both intermodal drayage operations and the repositioning of empty containers can be optimized at the same time.

To solve the drayage problem, we developed a real-time optimization model based on a genetic algorithm that operates with stochastic cost estimations, and we tested it with a series of drayage problems generated randomly. The genetic algorithm improves the initial solution, provided by an insertion heuristic, with an average improvement of around 2% in each dynamic iteration for the type of problems considered.

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