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A Multi-Agent System based on the Multi-Objective Simulated Annealing Algorithm for the Static Dial a Ride Problem

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Abstract: The Dial a Ride Problem (DRP) is to take passengers from a place of departures to places of arrivals. Different versions of the Dial a Ride Problem are found in every day practice; transportation of people in low-density areas, transportation of the handicapped and elderly persons and parcel pick-up and delivery service in urban areas. The ultimate aim is to offer an alternative to displacement optimized individually and collectively. Indeed the DRP is a multi-criteria problem, the proposed solution of which aims to reduce both route duration in response to a certain quality of service provided. In this work, we offer our contribution to the study and solving the DRP in the application using a multi agent system based on the Multi-Objective Simulated Annealing Algorithm. Tests show competitive results on (Cordeau and Laporte, 2003) benchmark datasets while improving processing times to obtain a pareto solution for the problem in concern.

Keywords: Heuristics, Dial a Ride Problem, Passenger Transportation, Multi-Criteria Optimization, Multi-Objective Simulated Annealing Algorithm, Multi-Agent System

1. INTRODUCTION

Starting with the indisputable observation regarding the increased travel demand of individuals, the available resources are no longer able to satisfy all users. For example, urban public transport is basically affected by their rigidity (ride scheduling would be the application that adapts to the offer). Inspite their role in avoiding the problems of public transport, individual vehicles have a negative face, as they are non-ecological and great-energy consumers. Indeed, individuals seeking ways to a more flexible transport that can meet their needs. The DRP can meet this expectation. It is considered as a collective-individualized transport activated on demand. A DRP consists in meeting the travel demands on a set of passengers scattered geographically. Each transport demand is modelled by a request containing the information on this last. This information is the number of passengers, points of departure and destination, and the time windows related to these points. The problem consists of determining the best routing schedule for the vehicles, which minimizes overall transportation costs while maintaining a high level of customer service.

The DRP is classified as NP-hard problem. So The exact methods are not able to solve such a problem in a reasonable time, especially as the problem size is important. In this case, we often use methods that find approximate solutions in reasonable time by applying heuristics and meta-heuristics, such as those based on genetic algorithms, simulated annealing, tabu search etc… (Cordeau and Laporte, 2006, Bervinsdottir, 2004, Baugh et al, 1998). In addition, it is a multi-criteria problem. So we need a multi-objective method to solve the DRP.

The multi-objective methods has a rather different aspect to scalar-objective one. Instead of finding one global optimum, which is a general aim in scalar-objective optimization, multi-objective methods must find a set of solutions, which is called the *Pareto set*, or *Pareto optimal frontier*, as all the Pareto solutions are equivalently important and all of them are the global optimal solutions. In our case, we use the Multi-Objective Simulated Annealing (MOSA) to solve the multi-criteria DRP.

In this paper, we present the modelization of the multi-criteria DRP. Subsequently we apply the MOSA algorithm in the vehicle agent of our multi-agent system to solve it. The second part is devoted to the presentation of the DRP. Then, in the third, we outline some previous works to solving the DRP in the static and dynamic contexts. In the forth section we present our mathematical model for the static DRP. The fifth section deals with the proposed multi-agent model. The organizational aspects of this model as well as the associated solving process are presented in this section. Then, the numerical results that prove the effectiveness of our approach is given in Section six. Finally, we conclude with some remarks and perspectives for this work.

2. THE DIAL A RIDE PROBLEM (DRP)

In our work, we consider the following dynamic DRP: every demand of transport define pick-up and delivery location, as well as preferred beginning of the service. Indeed the DRP is characterized by a set of transport demands of size *"n"* and a number of vehicles *"m"* to serve them. Each transport

demand is modelled by a request containing information on demand. To respond to this demand, we must recover a person from a starting point *"i"* and drop it in *"n+i"*. The departure *"i"* must start in the time window [a_i, b_i]. Delivery must be made within the time window *[a_{i+n}, b_{i+n}]*. In fact, the DRP is an extension of the Vehicle Routing Problem (VRP) (Debong and Qijun, 2008) (Boudali et al, 2004). Indeed in the DRP, we have an additional constraint which is the consistency of the order of vehicle passage to serve a request. For example, we obviously cannot pass across an arrival point of transport demand before carrying the person making the request. So the aim is to design a set of least costly vehicle routes capable of accommodating all requests, under a set of constraints. The most common constraints relate to vehicle capacity, route duration and maximum ride time, i.e., the time spent by a user in the vehicle. In our case, to execute the service, there is a homogeneous vehicles set with the same load capacity that cannot be exceeded. The passengers are picked and delivered by the same vehicle.

3. RELATED WORK

A DRP is an extension of the PDP (Pickup & Delivery Problem) where the transport of goods is replaced by the transport of persons (Krumke et al, 2006). Several versions of the DRP have been studied over the past 30 years. In the paper (Cordeau and Laporte, 2006), we find a more detailed presentation of the state of the art of this problem. The DRP has been widely studied in literature. In this section, we give a brief literature review on this issue.

When the problem size is small, we tend to use exact methods to solve it. In this context we cite the work of Psaraftis who used an exact algorithm of dynamic programming to solve the problem with one vehicle (Psaraftis, 1980). User inconvenience is controlled through a ''maximum position shift'' constraint limiting the difference between the position of a user in the list of requests and its position in the vehicle route. Only very small instances (n ≤ 10) can be handled through this algorithm. He studied the case where there are time windows imposed at pickups and delivery points for each request. Still with the exact methods, we find the work of Stefan who solved the DRP using the Branch and Bound method (Stefan, 2005). Desrosiers et al, 1991 further improve upon this methodology by performing the insertions in parallel, Dumas et al,1991 have extended their single-vehicle exact algorithm to the multiple-vehicle case and applied it to instances with n ≤ 55.

With the increase in travel demands in a DRP, researchers have decided to solve the problem using heuristics and meta-heuristics. These methods enable to reach an acceptable solution to the problem in a reasonable time. In this context, we mention major works such as those of Mauri et al, where the authors have resolved a multi-objective DRP (Mauri et al, 2006). They applied their approach on data derived from the benchmark presented in (Cordeau and Laporte, 2003). Indeed, they have developed a simulated annealing algorithm based on three methods of local search. Cordeau and laporte have applied the tabu search algorithm for solving the problem (Cordeau et al, 2003). Recently Claudio et al, have

developed a genetic algorithm for the DRP (Claudio et al, 2009).

The Multi-objective Simulated Annealing algorithm (MOSA) was not used to solve the DRP in the previous works mentioned in the state of the art. For this reason and the advantages of this algorithm we have chosen to apply it to solve this problem. Indeed the MOSA algorithm uses the domination concept and the annealing scheme for efficient search. Additionally MOSA can find a small group of Pareto solutions in a short time, this is important if you need a rapid response. Then find more solutions by repeating the trials for detailed information about the Pareto frontier.

4. MATHEMATICAL FORMULATION OF DRP

The DRP has been modelled mathematically in several research works. It is generally modelled by a multi-objective mathematical program. In this section, we present the mathematical modelling of our DRP. This model is characterized by two main objectives. The first one is economic, and the second is the quality of service rendered to travellers. In this work, we solve a multi-objective DRP using the MOSA algorithm. In the follows part, we present our mathematical formalization of the problem

- Variables of DRP

n: Number of transport requests, P= {1 . . . n}: Pickup locations, D = {n + 1, . . . , 2n}: Delivery locations, M: set of vehicles depots, N= D $\cup$ P $\cup$ M: The set of all nodes in the graph, Request *i* consist of pickup *i* and delivery *n + i*, V_i: set of nodes visited by a transport demand i, V: Set of vehicle, Q_v: Capacity of a vehicle v, [a_i b_i] : Time window of pickup point of demand, [a_{i+n} b_{i+n}] : time window of delivery point of demand, q_i : number loaded onto vehicle at node *i*. $q_i = q_{n+i}$, T_{ijv}: Travel time from *i* to *j* with the vehicle *v* T_{aiv}: Arrival time for the request *i* with the vehicle v, T_{siv}: Start time of service for the request *i* with the vehicle *v*, NSV_i = The number of stations visited by a transport demand i, L_{iv}: The load of vehicle *v* after visiting node *i*, $C_{ijv} = C_{ij} \times C_v$: Cost of travel from *i* to *j* with the vehicle *v* such that C_v is the cost of using vehicle *v*, X_{ijv}: Decision variable of the problem, X_{ijv} = 1 if the vehicle v takes a direct path from *i* to *j*, else $X_{ijv} = 0$

- The Multi-objective function

The Multi-objective function: Economic criterion + Service quality criterion

- Economic criterion

$$\text{ECO} = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V} X_{ijv} C_{ijv} \qquad (1)$$

- Service quality criterion:

The Service Quality (SQ) criterion is composed by two major's criteria, the first one is the Ride Time (RT) criterion

and the second one is the Number of Stations Visited (NSV) criterion. In our formulation for the DRP, we don't attribute weights to the objectives of the problem because we use the domination concept in the resolution of the multi-criteria DRP. Indeed the proposed approach does not use an aggregative method to solve multi-criteria problems. It applies the concepts of Pareto optimality and a-efficiency to find the best compromise solutions to the problem. So, it reduces the set of possible solutions for the considered problem.

$$SQ = RT + NSV \tag{2}$$

RT: Ride Time
NSV: Number of Stations visited

With

$$NSV = \sum_{i \in D} NSV_i \tag{3}$$

$$RT = \sum_{i \in D} \sum_{v \in V} (T_{aiv} - T_{siv}) \tag{4}$$

We can rewrite RT (3) using the decision variable X_{ijv}

$$RT = \sum_{i \in D} RT_i \tag{5}$$

As

$$RT_i = \sum_{i \in V_i} \sum_{j \in V_i} \sum_{v \in V} X_{ijv} T_{ijv} \tag{6}$$

5. DEVELOPED APPROACH

In our work, the decision evaluation problem is regarded as a multi-criteria optimization one (Collette and Siarry,2002) for which we propose a non aggregative approach .This approach is based on the Multi-Objective Simulated Annealing Algorithm (MOSA) . We detail the MOSA algorithm in the subsection 5.2.1.Indeed, our approach benefits from the multi-agent techniques (Clearwater et al., 1992; Wooldridge, 2002) that have opened an efficient way to solve diverse problems in terms of cooperation, conflict, negotiation and concurrence within a society of agents.

The approach based on the multi-agent system developed in this research is composed by 3 major's agents. This distribution using a multi-agent system makes the possibility to find the global optimum for the DRP. Indeed, the vehicle agent and the dispatching centre agent do an optimization task in the resolution of this last. The first one is client agent who sends a request to the Dispatching centre agent. The dispatching centre agent broadcast this request for all the vehicle agents. The vehicle agent make an optimization process based on the MOSA algorithm detailed in the

5.1. Optimization with the Multi-Objective Simulated Annealing (MOSA): Agent vehicle

The hardness of the problem depends on the number of transport demands N to serve for every moment in the workday. When N is small, traditional mathematical programming approaches can be used to obtain the real optimal solution of DRP; however, when N is large, it is not possible to do that. Therefore, researchers have developed various algorithms that can finish performing within polynomial time to find the problem initial feasible solution and then apply the meta-heuristic approach to obtain an approximate global optimum solution.

In this research we develop an approach based on the Multi-Objective Simulated Annealing (MOSA) algorithm to solve the DRP in the agent vehicle. So the MOSA algorithm produces an itinerary for the vehicle to serve the affected transportation demands.

The Simulated Annealing (SA) algorithm is a method following the process used in metallurgy. SA algorithm was originated by Metropolis et al (Kirkpatrick et al, 1983). SA was developed from the so-called "statistical mechanics" idea. Annealing is the process through which slow cooling of metal produces good, low energy state crystallization, whereas fast cooling produces poor crystallization. The optimization procedure of simulated annealing reaching an approximate global minimum mimics the crystallization cooling procedure. SA is classified among the research methods operating locally; it can make changes to the current solution to exit a local optimum. Generally, suddenly reducing high temperature to very low (quenching) cannot obtain this crystalline state. In contrast, the material must be slowly cooled from high temperature (annealing) to obtain crystalline state. During the annealing process, every temperature must be kept long enough time to allow the crystal to have sufficient time to find its minimum energy state. The local search continuously seeks the solution better than the current one during the searching process.

The approach based on the (MOSA) algorithm developed in this agent is composed by 3 major's procedure. The first procedure is used to get an initial solution of problem. The initial solution of the MOSA algorithm is generated by a distribution heuristic. In the second procedure is the neighbourhood structure. It is used in the MOSA algorithm to generate a neighbourhood solution to improve the current solution of the DRP.

MOSA uses the domination concept and the annealing scheme for efficient search. Indeed MOSA have an obstacle in multi-objective optimization, is its inability to find multiple solutions.

However, MOSA can do the same work by repeating the trials as it converges to the global optima with a uniform probability distribution in the single objective optimization. By cons MOSA has advantages over evolutionary algorithms (EAs) because it does not need a large memory to keep the population; and the MOSA algorithm does not use additional algorithms to spread the solutions over the Pareto frontier. Indeed MOSA can find a set of Pareto solutions in a short time this is important if you need a rapid response, and then find more solutions by repeating the trials for detailed information about the Pareto frontier.

The pseudo-code of implemented MOSA algorithm is described in figure 1:

```
1. GIVEN (α, Iter-MAX, T0 ,TC) DO
2. CREATE (a initial solution S using distribution heuristic method);
3. IterT ← 0; {Iterations number at temperature T}
4. T ← T0; {Current temperature }
5. WHILE (T > TC) DO
6.      WHILE (IterT < Iter-MAX) DO
7.          IterT ← IterT + 1;
8.          CREATE (any neighbour S' to S using Neighbourhood
Structure);
9.          IF (C(S') dominates C(S)) S ← S';
10.         ELSE IF (x < Pt) S ← S';
            ELSE IF (C(S') not dominates C( S) and C(S) not   dominates
            C( S') S ← S';
11.         END-IF;
12.     END-WHILE
13. T ← α * T; IterT ← 0;
14. END-WHILE
15. RETURN (S);
```

Fig. 1. Multi-Objective Simulated Annealing algorithm.

Where $x \in [0\ 1]$: randomly value used to calculate the probability to move to a neighbourhood solution S', $0 < \alpha < 1$ is a cooling rate, Iter-MAX: the number of iteration for each temperature, T0: the initial temperature, TC: the final temperature, C: the cost objective vector, P_t: The transition probability from solution S to neighbourhood solution S'.

General transition rules such as the Metropolis or logistic method cannot be applied directly to the multi-objective problems because they support only a scalar cost function. The suggested transition rule in this paper is very similar to the Metropolis method except that they used a different cost criterion for the multi-objective cost function. The transition probability from state i to j is,

$$P_t(i, j) = \exp(-c(i, j)/T) \qquad (19)$$

where $c(i, j)$ is the cost criterion for transition from state i to j, and T is the annealing temperature. Six criteria for MOSA are suggested and evaluated.

- Average cost criterion

$$c(i, j) = \frac{\sum_{k=1}^{D} (c_k(j) - c_k(i))}{D} \qquad (24)$$

In this work we use the average cost criterion because we tested the above six criteria and found that average criterion show good performance.

5.1.1 Initial solution

In our work, we use a distribution heuristic to create the initial solution of the problem. This heuristic may violate some constraints as the vehicle capacity and the respect of time windows on pickups and deliveries points. Indeed, in our approach we start from an initial solution that does not necessarily satisfy the constraints of the problem. These constraints will be satisfied by the process of finding neighbourhood solutions for the initial solution using the neighbourhood structure. This method create randomly the

schedule of the vehicle to serve the transport demands affected to this last.

5.1.2 Neighbourhood Structure

To improve the solution of the DRP, we must make changes to the current solution. These changes are made by a neighbourhood structure. In the simulated annealing algorithm can accept change even if they degrade the quality of the solution to escape the local optimum. Our neighbourhood structure is the re-order route based on the method found in the work (Bergvinsdottir, 2004). It is interesting to highlight that in these moves the depots are not considered, because they are "fixed" in all the routes, and thus their positions cannot be changed. The Re-order route move consists basically in selecting any route from solution, select any point in this route, select a new position for this point and change this point position with the new position.. The selected point can be a pick-up or a delivery point.

5.2. Local search optimization: dispatching centre agent

The dispatching centre agent sends every request of transport to all the available vehicle agents. After sending the request, the dispatching centre collects all the responses from vehicles and it choose the best one using the domination concept. With this local search, we more explore the search space by the fact of collecting many solutions from vehicles and choosing the best one.

6. COMPUTATIONAL RESULT

In this work, we chose to test our approach to data presented in (Cordeau and Laporte, 2003) (available in: <http://www.hec.ca/chairedistributique/data/darp />). Indeed, in this benchmark, we find 20 instances of DRP. These instances are diversified by the number of transport requests and the number of vehicles. The size of these instances of problems is ranging from 24 to 144 requests. In Table 1, we give the values of the parameters of the Multi-Objective Simulated Annealing algorithm (MOSA).

Table 1. The parameters of MOSA

Parameter	Value
T0	3000
α	0.975
TC	0.001
Iter-MAX	1000

The parameters of MOSA are chosen after several tests applied to the problems affecting each time new values to parameters. In Table 1 we present the values of parameters leading to good results. We denotes by T0: the initial temperature, α: cooling rate, TC: the final temperature and Iter-MAX represent the iteration number for each temperature.

5.1 Obtained Results

The best obtained results (Table 2) are still compared to the obtained by (Claudio et al, 2009) and (Cordeau and Laporte, 2003). In the work (Claudio et al, 2009), the authors have applied the Genetic Algorithm (GA) to solve the DRP. In (Cordeau and Laporte, 2003), the Tabu Search algorithm (TS) is applied to solve the concerned problem.

Table 2 shows the results obtained by our work while Tables 3 and 4 show the results obtained by the previously mentioned researches. Because the compared models do not have the same characteristics, the comparison was done on the basis of time units of two critical factors: On the one hand, the total route duration that is associated with the transport system resources optimization, and on the other hand, the total client travel time (ride time) that is associated with the offered quality of service.

Table 2. Summary of the results obtained by our approach: MOSA algorithm

Instance	**Best** Route Duration (min)	**Best** Ride Time (min)	CPU time (min)
Pr01	932,73	516,19	1,12
Pr02	1825,39	731,2	3,29
Pr03	2806,70	3546,64	12,30
Pr05	3809	2785	10,56
Pr11	1003,77	598,13	1,53
Pr12	1366,43	811,50	5,62
Pr15	4051,60	3001,2	16,20
Pr16	4512,30	2247	15,21
Pr17	13397,50	933,58	3,60
Pr019	3312.70	2894	14

Table 3. Summary of the results obtained by Genetic Algorithm (GA) of (Claudio et al, 2009):

Instance	**Best** Route Duration (min)	**Best** Ride Time (min)	CPU time (min)
Pr01	955,25	524,59	1,36
Pr02	1839,06	838,41	4,08
Pr03	2787,18	1597.95	7,96
Pr05	4068,05	2935,48	18,43
Pr11	902,18	449,91	1,58
Pr12	1503,34	744,93	4,49
Pr15	4057,08	3152,67	22,09
Pr16	4658,64	2348,48	17,48
Pr17	1223,68	612,40	3,13
Pr019	3427,06	2515,53	25,43

Table 4. Summary of the results obtained by Tabu Search (TS) of (Cordeau & Laporte ,2003)

Instance	**Best** Route Duration (min)	**Best** Ride Time (min)	CPU time (min)
Pr01	881	1095	1,9
Pr02	1985	1977	8,06
Pr03	2579	3587	17,18
Pr05	3870	6154	46,24
Pr11	965	1042	1,93
Pr12	1565	2393	8,29
Pr15	3596	6105	54,33
Pr16	4072	7347	73,7
Pr17	1097	1762	4,23
Pr019	3249	5581	51,28

For validation of the proposed multi-agent system and MOSA application in the vehicle agent to solve the DRP, 5 tests were performed for each instance. Table 1 presents a summary of the best obtained results in these tests. In this table, the column *Best Route Duration* indicates the value of economic objective function for the best solution found in the 5 tests (for each instance). The column *Best Ride Time* presents total client travel time, and the column *CPU time* presents the time to get a solution for the DRP.

We note that in the some instances, our approach is more efficient than the approach implemented in (Claudio et al, 2009). The values outlined in our summary of results, foresee cases where our approach is better than (Claudio et al, 2009). Indeed when we based on the number of individual results for the *Route Duration*, our approach based on the MOSA algorithm shows better results than GA in (7/10) times and worse than TS in (7/10) times. For the *Ride Time,* our approach MOSA shows better results than TS in (10/10) and equal to GA. when we based on the total time for the *Route Duration*, our approach MOSA is worse than GA (11596,6 mn). For the *Ride Time,* our approach MOSA is worse than GA (2492 mn) and better than TS (18830 mn).

As exposed in the results section, our MOSA implementation presents better results than obtained in (Claudio et al, 2009) for the route duration time. This is mainly due to the use of time-windows as hard constraints and the use of the domination concept for the multi-objective optimization. But our approach MOSA shows worse results than TS implementation (Cordeau and Laporte, 2003) for the route duration time. This can be understood by the factor of using an aggregative method with a big weight assigned to the route duration objective to solve the multi-criteria DRP in the TS implementation and the cost of having good average ride times for clients, as there is a trade-off relation among both variables. From other point of view, it can be seen as a search with memory, as in Tabu search. However, in this case the memory is used for making the algorithm to "remember" which portions of sequences are feasible in order to reduce effort instead of remembering the solutions found so far to avoid local optima.

When focusing on the ride time our solution showed equal times (5/10 times) regarding the Genetic Algorithm (GA) of Claudio et al. This can be understood as the use of time-windows as soft constraints in the GA implementation while obtaining better results when compared to the TS solution (Cordeau and Laporte, 2003). This can be understood as the cost of having good average ride times for clients, as there is a trade-off relation among both variables and the

optimization in the vehicle agent and the dispatching centre agent in our Multi-agent system.

It is worth highlighting that the tests were performed in a laptop Dell B14DEE640C with Intel Intel Core 2 Duo of 2.0GHz processor and 2GB of RAM memory. The whole implementation was developed in the JADE Multi-agent platform and using the JAVA language, while the Claudio et al,2009 tests were done with a 2.66 GHz Intel Pentium 4 CPU .The Cordeau and Laporte tests were done with a 2.0 GHz Intel Celeron CPU. Although the hardware configurations are dissimilar, they do not completely justify the time improvement.

6. CONCLUSION AND PRESPECTIVES

This work presented a new approach based on the multi-agent system to solve the dial-a-ride problem. The proposed model was able to represent the problem in a generalized mode, and it was easily adapted to other models already known.

In this paper, we proposed a mathematical model for the multi-objective DRP. Indeed, we have proposed a multi-agent system based on the Multi-Objective Simulated Annealing algorithm for solving the DRP. The clustering and routing were performed by the local search procedure and the neighbourhood structure.

After applying our approach on a benchmark presented in (Cordeau and Laporte, 2003), we have had good results in short computing times. The resulting method was compared to the results given by Claudio et al, 2009. The comparison focused on the route duration and the ride time.

However, improvements can be made about our approach:

Resolution of the problem with heterogeneous vehicles to assign each customer to the appropriate vehicle.

The application of this approach to real problems

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