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A Distributed Approach for resolving a Stochastic Dial a Ride Problem with NSGA II

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***Abstract*: Transportation on demand does not stop facilitating our daily life. In fact, for 40 years the research has contributed to the resolution of the Dial a Ride Problem to improve the service offered to customers. In this research, we contributed to the resolution of a Stochastic Dial a Ride Problem while consider four problems that may inhibit the proper functioning of service Transport on Demand , such as accidents, congestion, inadequate number of places in vehicles and breakdowns. Dial a Ride Problem is known as an NP-hard problem. So the exact resolution with large instances will be very expensive. Therefore, the use of heuristic will be beneficial. In this paper, we present a mathematical model aims to describing and resolving the Stochastic Dial a Ride Problem and the development of a meta-heuristic based on NSGAII hybridized with a stochastic process to minimize the distance traveled by vehicles and the elapsed time also to maximize the quality of service while minimizing the risk that rates that may penalize the smooth functioning of the transport service.**

***Keywords*:** Stochastic Dial a ride Problem “SDRP”; Genetic Algorithm “GA”; Meta Heuristics ‘’MH’’; Distributed Artificial Intelligence “DAI”; Multi-Objective Optimization “MOO”; Multi-Agent System “MAS”; Transport On Demand Simulated Annealing “TOD-SA” ; Transport On Demand Genetic Algorithm kind NSGAII “TOD-GA”.

I. Introduction

Public transport is continuously trying to facilitate our daily lives. Therefore it has become a necessity to enhance those services in order to account for their efficacy. The Commission on Sustainable Development of Economic and Social Council of the United Nations says that transport can have negative consequences on the environment at local, regional and global levels , as well as on health, noise ones and land use [27]. Thus, the improvement and optimization of the existing transportation system appear as a necessity. But the complexity of the transport system is real and reports social, economical and structural phenomena that should be understood in the entirety of their interactions. This makes the task of providing solutions to some transport-related problems even more difficult. Besides, the situation descends into further aggravation due to the nature of the Transport on Demand " TOD" which integrates terrestrial modes (road and rail, sea and air) and concerns people more than goods. The resolution of a SDRP is an alternative transport solution for increasing occupancy vehicles. This increase is a part of the fight against traffic congestion. It helps to reduce the emissions of greenhouse gases, and therefore the reduction of environmental pollution. TOD is economically profitable since the cost of transportation is focused on individuals soliciting this service.

The problem addressed in this research is a Stochastic DRP. In fact we take into consideration the failures of vehicles, accidents and traffic congestions, etc...

In the first part of this work, we will move forward to analyze and identify suitable vehicles (which have a high probability) to take responsibility for requests from passengers to transport them in the best conditions. The second will highlight some significant literature reviews. Section 3 will describe our approach which is based on the genetic algorithm of the kind NSGAII. In Section 4, we will detail the numerical results obtained. Finally, we will present the conclusion and some perspectives related to this contribution.

II. Related works

Before quoting the work of research that has contributed to the resolution of the stochastic DRP, we need to recall the specifics of this problem. Indeed, the DRP is an extension of Vehicle Routing Problem (VRP) which has an additional constraint which is the consistency of the order of passage of a vehicle to serve a request. The resolution of the DRP is to determine and plan the tours realized by vehicles to satisfy the demands of passenger who want to be transported from origin to destination. The latter is characterized by a set of transport demands size « n » and a number of vehicles « m » to serve them. Each transport on demand is modeled by a query containing information on demand. The execution of a query is to support a person from the pick-up point «i »and drop him at the point «i+n ». It is obvious that we cannot go to a delivery point before recovering the person making the request.

The DRP with a single vehicle has been formulated with an entire program by Desrosiers, Dumas and Soumis [16]. In this formulation, there are constraints of time window and vehicle capacity and precedence constraints. The authors have solved the problem by dynamic programming. Optimal solutions were obtained for a number of transportation requests equal to 40.

DRP with multiple vehicles [17] is solved by Cordeau and Laporte who presented a heuristic algorithm based on Tabu search. In their work, users specify a time window for the time of arrival and start their journey. Tabu search algorithm based on iterative removal of transport demand and reintegration into another route.

Psaraftis also studied the dynamic DRP [13]. In the dynamic DRP new transport requests are generated dynamically over time, but no information on future requests are available. So the problem is to re-optimize the portion of the solution after time t, including the new application. A practical difficulty which paralyzes this approach is the possibility to solve the problem at time t before the arrival of the next request. This can only be possible if the algorithm is heavy and requests arrive quickly. Psaraftis worked on dynamic DRP helped define the concepts used in the research done on dynamic routing problems treated in [14] [25].

Four heuristics have been published to solve the DRP several vehicles. Rekiek, Delchambre and Salehaim to reduce the number of vehicles used to serve travelers. The authors presented a genetic algorithm for the consolidation phase of travelers and an insertion mechanism for the routing phase. They tested their approach on actual data from the city of Brussels [6].

Mguis, for solving a Problem Vehicle Routing in an emergency, proposed a multi-agent approach. The context of this problem is to plan a tour together to serve a heterogeneous set of applications by providing for contingencies such as the arrival of a new application and / or the occurrence of a disturbance. Although he made a study of future states to prevent it but he did not use the stochastic [10]. Although in approach Raddaoui et al used the NSGA II and obtained promising results. However, they did not take into consideration the possible problems that occur to vehicles during tours [3]. In 2012, Amara et al proposed a hybrid approach based on GA to select the relevant features in an OCR system [20].

DRP solved by Teodorovic Radivojevic et al ignores a well-defined objective function [9]. Indeed, the DRP resolved processes a set of three criteria to minimize: distance, waiting time of vehicles and journey times for passengers.

Three different objectives of dynamic DRP were tested by Colorni and Righini, namely improving number of transportation requests served, maximizing the perceived level of service passengers, and the minimization of the distance [2].

In 2002, a program was developed by Horn for transport services on demand. The software developed gives good results on large instances [21].

In 2004, Attanasio et al proposed a parallel algorithm for dynamic DRP. At the beginning of the planning period and using a tabu search algorithm, a static solution is chosen. When the arrival of a new application, each thread inserts the request of a randomly chosen solution in the current tabu search and rerun to obtain a feasible solution. If a feasible solution was found, the request is accepted and a phase of post-optimization re executed [1].

An algorithm was developed by Coslovich, Pesenti and Ukovich followed a two-phase strategy for the insertion of a new transport demand in an existing route [18]. An off-line phase is first used to create all possible routes on the known based on the mechanism of optimization applications. After an on-line phase is used to insert the new application taking into account the objective of minimizing user dissatisfaction. The weak points of procedure is that the capacity constraint and response time are not considered.

Besides, we notice that the application of the stochastic is distinguishable in the field of industry and more specifically in the field of artificial intelligence. For the stochastic DRP some approaches have been developed, including one conducted by TAN who studied the DRP mathematically in the third and the fourth part of his thesis. He had used the notion of stochastic resolution to minimize the cost, but only for the routing problem of the TOD, not for possible problems that could inhibit the proper functioning of the vehicle [28].

In the work of Prodhon Carolina [8] the transportation problem has been treated in a different way. In fact Prodhon considers that it is a problem of transport logistics which implies two levels of decision. The first level is the location of deposits (strategic level) and the second level is the development of vehicle routing (tactical or operational level).Therefore its purpose is limited to the optimization of the aircraft movement. This work, however, does not address the problems of transportation, although this approach was based on stochastic concepts.

Xiang, Chen Chu solved a version of DRP using stochastic, but their contribution is limited to adding additional constraints for drivers: breaks, qualification degrees according to queries. But in their research they did not take into consideration the safety of travel (stroke) [29].

Fu was interested in stochastic variations of travel times in order to improve the existing TOD system without taking into account other possible problems such as failure, bottling and so on. [19]

Issaoui et al have contributed to the resolution of DRP using a stochastic approach based on simulated annealing. Their approach rather than only taking into account the concept of stochastic, it has also stressed the possible problems during tours. [5]

Remy Chevrier has contributed to the resolution of DRP based on the principle of convergence of flow from the polarized nature of the territory. He offered deployment methodology TOD operator on the one hand the theory of graphs and other genetic algorithms on the other hand. [24]

In the light of our thorough search in the literature, we did not find a work that applies the concepts of stochastic to escape from the possible risks related to the TOD (breakdown, accidents, congestion, occupation). Only the work, evoked by Issaoui et al, solves the stochastic DRP but their approach is based on simulated annealing. Just Issaoui et al in [4] contributed to resolving the DRP with NSGAII.

In this section, we will detail the problems that may cause malfunctioning of the service of TOD, and we will explain our approach.

A. Modeling the proposed solution

1) The accident

Accidents are very common and can severely damage the car. Suppose that all the cars are in good condition, there are other factors outside of the car components that may cause accidents such as the climate and roads. These factors are not the only ones but are most often responsible for the accident.

Fig. 1 shows a graphical representation of the causes leading to the accident.

Figure 1. Accident Schema

Climate and road are themselves factors that can affect the quality of everyone that we do not learn. Our interest will be focused on the possibility of having an accident.

2) The failure (breakdown)

The accident is not the only factor that can lead to stopping the vehicle. The vehicle, at any time, can have a failure which can be caused by several factors. We will mention the most important ones. Failure means the vehicle has stopped.

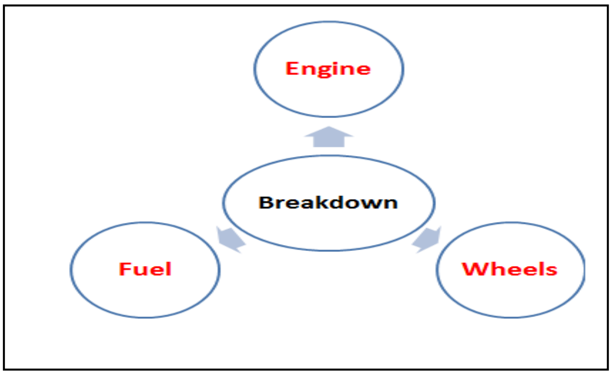

Figure 2. Failure schema

The engine, gasoline and wheels have themselves some causes that are responsible for the quality of each one. In this work we are interested only in the final state of the car. This leads us to respond to the question" Is there a failure in the car?".

3) The Bottling

So far, we have seen up until now two factors responsible for possible problems for vehicles. If the car is in good condition and the possibility of having an accident is zero, this does not guarantee that the vehicle is operating normally, and that it will meet the demands of passengers as soon as possible. A third factor involved, responsible for the good or bad operation of the system is all traffic. It has specific properties that we will discuss in the next section. Fig. 3 shows a schema of the factors bottling.

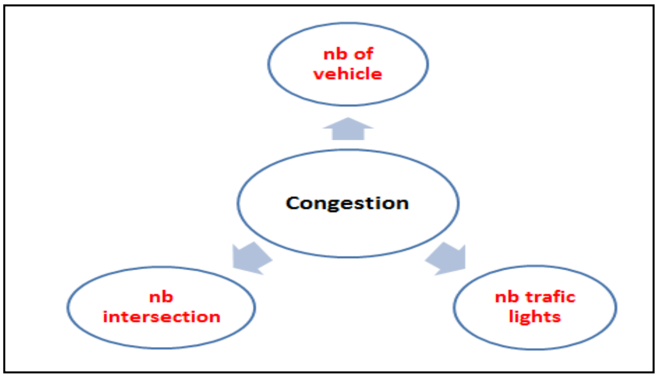

Figure 3. Bottling schema

In this article we are not interested in detailing the factors related to bottling. We will just try to answer the question «Is there a traffic jam? ».

4) The Occupation

The last three factors (breakdown, accident and congestion) do not lead alone to system malfunction; the occupation of the car is a key factor which guarantees the proper functioning of the service. So the existence of places in the car to serve passengers is a necessary peace of information that can be employed to avoid possible problems for the car service. That factor has properties which we will detail in the following section.

Busy state and Non Busy State

This is measured by the number of spaces available in the car. If this number is equal to the maximum possible, so the state is occupied and vice versa.

Fig. 4 shows a schema of the occupancy factors.

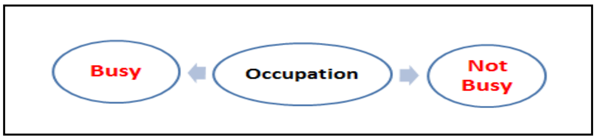

Figure 4. Occupation schema

B. *Mathematical formulation for the stochastic study*

We have studied the possible problems that can happen to the vehicles mathematically, and more precisely by determining the probability of each. Recall that Ω is the set of all possible outcomes that can be achieved in a random execution. Accident is represented by the random variable: X (i) denotes the critical values that allow us to determine the probability of malfunctioning of this criterion.

While the range of variation is Ω becomes $\Omega \rightarrow \{a, b\}$.

We have the following situation:

Events a and b are independent and compatible. Then $P(a \cap b) \neq 0$ and $P(b \cap a) \neq 0$. So here we have two values to calculate. But we can neglect P $(b \cap a)$ because the probability of route seems more important than the probability of climate. It suffices then to find the value of P (a | b).

Table 1. Random variable for accident

Criterion	Road	Climate
X(i)	a	b
P(X$_i$)	P(a)	P(b)

The failure is represented in the same way as the previous event by the random variable: X (i) denotes the critical values that allow us to determine the probability of failure. So the range of variation is Ω becomes Ω → {a, b, c}.

We have the following situation:

Events (a and b) and (b and c) are incompatible (disjoint); There is no semantic link between them. Then P (a ∩ b) = P (b ∩ c) =0 and P (a ∩ c) ≠ 0. So we just search P (a | c).

Table 2. Random variable for failure

Criterion	Engine	Wheels	Gasoline
X(i)	a	b	c
P(X_i)	P(a)	P(b)	P(c)

Bottling is represented in the same way as previous events by the random variable, such that X (i) denotes the critical values that allow us to determine the probability of failure.

So the range of variation is Ω becomes Ω → {a, b, c}

We have the following situation:

Here all the events are not disjoint and independent. So we must look for the values P (a | (bUc)), P (b | (aUc)) and P (c | (aUb)).

Table 3. Random variable for bottling

Criterion	nb of cars	nb of red lights	nb of cross roads
X(i)	a	b	c
P(X_i)	P(a)	P(b)	P(c)

.

The occupation is represented in the same way by the following random variable, such that X (i) denotes the critical values that allow us to determine the probability of bottling.

While the range of variation is Ω becomes Ω → {a, b}

We have the following situation:

Events a and b are independent and compatible. Then P (a ∩ b) ≠ 0 et P (b ∩ a) ≠ 0.

So here we have two values to calculate. But we can neglect P (b ∩ a) because the probability P (a ∩ b) is sufficient to infer the state of the car. It suffices then to find the value of P (a | b).

Table 4. Comparison of results

Criterion	Busy	Non Busy
X(i)	a	b
P(X_i)	P(a)	P(b)

All these functions calculations and the NSGAII algorithm are executed by agent vehicle. In the next section, we will detail the specific operation of a vehicle agent.

C. Proposed objective functions and algorithms

1) Variables of the DaRP

n : Number of transport requests.

D=1..n: Set of recovery points travelers.

P=n+1,..,2n: Set of points of arrival of travelers.

M=0,..,m: Set of deposit containing vehicles.

N=D ∪ A ∪ M: Set of all nodes of the graph G (N, Ar) with A_r is all the edges of the graph.

V=0,..,v: set of vehicles.

Q_v: Capacité du véhicule v.

q_{vi} : Number of people were taken by vehicle v of the station "i" such that "i" ∈ D.

[a_i b_i] : Time window associated to the starting point "i" such that "i" ∈ D.

[a_{i+n} b_{i+n}] : Time window associated with the arrival point i+n such that i+n ∈ D.

$Cost_{ijv} = Cost_{ij} \times Cost_v$: Transportation cost from "i" to "j" with the vehicle "v" such that $Cost_v$ is the mileage cost of use of the vehicle.

T_{ijv}: Transport time from "i" to j with vehicle v.

T_{siv}: Start time of the service request "i" with the vehicle "v".

T_{aiv}: Arrival time of the request "i" to the vehicle "v".

NSV_i: The number of stations visited by a transport request "i".

L_{iv}: Number of passengers in the vehicle after visiting "i" as "i" ∈ N.

A_{ijv}: Decision variable of the problem, Aijv = 1 if the vehicle is traveling on a direct path from i to j, otherwise Aijv = 0.

2) Objective function

We have three objectives: The first and the second objectives are economic models of the entire distance traveled and the time taken for the journey. The latter concerns the quality of service in terms of the allocation of good vehicles to passengers.

The economic objective's function taking into account the quality rendered to travelers is written as follows:

The global objective function is the sum of the economic function and the quality of service; F = ECO + Fglobal

ECO= F1+F2

with

$$F1 = \sum_{i\in N}\sum_{j\in N}\sum_{v\in V} Cost_{ijv} A_{ijv} \quad \textbf{\textit{(1)}}$$

$$F2 = \sum_{i\in D}\sum_{v\in V}\left(T_{aiv} - T_{siv}\right) \quad \textbf{\textit{(2)}}$$

The third objective function is to optimize the allocation of suitable vehicles to passengers.

$$\mathbf{F_{global}} = \min_{i:1..m}\left(F_{profil}\left(?\right)\right)(\mathbf{F_{profil}}(i)) \quad (3)$$

Taking the min Fprofil(i) such as "i" an index denotes the starting of the vehicle number 1 until the final vehicle "m".

With Fglobal is the overall function searched by the vehicles.

Fprofil(i) is the elementary function which means the profile of each vehicle relative to the problem.

Therefore, every car is supposed to calculate the profile summing the different probabilities, the means, the sum of the probability of failure P(pn), the probability of having an accident P(acc), the probability of getting caught in a traffic jam P(con) and the probability of occupation of the car P(occ).

Fprofil (i) = Σ(P(pn); P(acc); P(emb); P(occ)).

A question arises for the field variation. What is the range of variation in which these probabilities vary?? The answer is as follows. We will divide the Fprofil by four with respect to the fact that the value of the probability obtained is always between 0 and 1.

Fprofil (i)= Σ(P(pn); P(acc); P(emb); P(occ))/4

And of course, if we find ourselves in a situation of equality, it affects one of the two cars on Fprofil in question.

$$F=\left(\sum\left(P(pn)+P(acc)+P(con)+P(occ)\right)/4\right)$$

$$+\ \left(\sum_{i\in N}\sum_{j\in N}\sum_{v\in V} Cost_{ijv}A_{ijv}\right)+\left(\sum_{i\in D}\sum_{v\in V}\left(T_{aiv}-T_{siv}\right)\right) \quad (4)$$

3) The constraints

$$\sum_{v\in V}\sum_{j\in N} X_{ijv}=1 \quad \forall i\in D \quad (5)$$

A vehicle "v" leaves only once the departure station "i"

$$\sum_{j\in D\cup P} A_{ijv}-\sum_{j\in D\cup P} A_{j,n+i,v}=0 \quad \forall v\in V,\forall i\in D \quad (6)$$

If a vehicle "v" serves a departure request "i", it certainly reaches the point of arrival "i+n".

$$\sum_{j\in D\cup P} A_{ijv}-\sum_{j\in D\cup P} A_{ijv}=0 \quad \forall v\in V,\forall j\in P\bigcup D \quad (7)$$

If a vehicle arrives at a node "v_i", it leaves the latter.

$$A_{ijv}(\mathrm{T_{siv}}+\mathrm{T_{ijv}}-\mathrm{T_{sjv}})\le 0 \quad \forall v\in V,(\mathrm{i},j)\in Ar \quad (8)$$

Vehicle "v" starts the service "j" after finishing the service "i" and follows the edge (i, j).

$$\mathrm{a_i}\le \mathrm{T_{siv}}\le b_i \quad \forall i\in N,\forall v\in V \quad (9)$$

Vehicle "v" must respect the time window of a node "i" in order to serve it in time.

$$\mathrm{a_{i+n}}\le \mathrm{T_{aiv}}\le b_{i+n} \quad \forall i\in N,\forall v\in V \quad (10)$$

A vehicle "v" must respect the time window of a destination node "i + n".

$$A_{ijv}(\mathrm{L_{iv}}+q_{\mathrm{vj}}-L_{\mathrm{jv}})\le 0 \quad \forall v\in V,(\mathrm{i},j)\in Ar \quad (11)$$

Conservation of the number of persons transmitted on a path (i, j) by a vehicle "v".

$$q_{\mathrm{iv}}\le L_{\mathrm{iv}}\le Q_v \quad \forall i\in D,\forall v\in V \quad (12)$$

The number of people present in the "v" vehicle after visiting "i" is higher than that collected in the "i" and less than the maximum capacity of the vehicle.

$$0\le L_{\mathrm{n+i,v}}\le Q_v-q_{iv} \quad \forall n+i\in D,\forall v\in V \quad (13)$$

The number of people in the vehicle "v" after visiting "i + n" is less than or equal to the capacity of the vehicle minus the number of people caught in the request "i".

$$L_{mv}=0 \qquad \forall m\in M,\forall v\in V \quad (14)$$

A vehicle "v" leaves vacuum of a deposit "m".

4) System architecture of Stochastic TOD

Now with the use of the same system in different areas we need distributed information systems, hybrid, heterogeneous, dynamic character and with rich semantic, varied and scalable. For this purpose the static programming hardly meets our needs.

For solving transportation problems, there are several researches based on MAS. Among the applications developed using multi-agent technology, we find Mnasri et al [26] whom contributed to the resolution of the Dynamic Discrete Berth Allocation Problem, and Mguis et al [11] whom resolved the vehicle routing problem in a disaster case.

To assist the regulator in regulating matches Saussol modeled a network of urban transport by MAS [7]. In fact, an agent models an active entity of the transport process. It can be a bus agent, station, depot and section interface.

Still remaining within the scope of the regulation of correspondence, Laïchour presents a multi-agent model is based on three types of agents [12]:

- The acquisition agent, which performs the data management crossings at bus stops regulation;

- Correspondence agent, who is responsible for the detection and diagnosis of disturbances in correspondence and the proposed decisions;

- The supervisor agent, which has a role of interface between the controller and help to regulate correspondence system.

In 2001, Gruer proposed an approach based on MAS for modeling and simulation of transport systems [23]. This system is composed of bus agents, stop and style.

In 2005, El Hmam et al adopted the agent paradigm to model the traffic flow at the microscopic level [22].

The use of agents in our system of TOD can be explained by two reasons: The first is that the DRP is an NP-hard problem. The second reason is explained by the dynamicity of system of TOD.

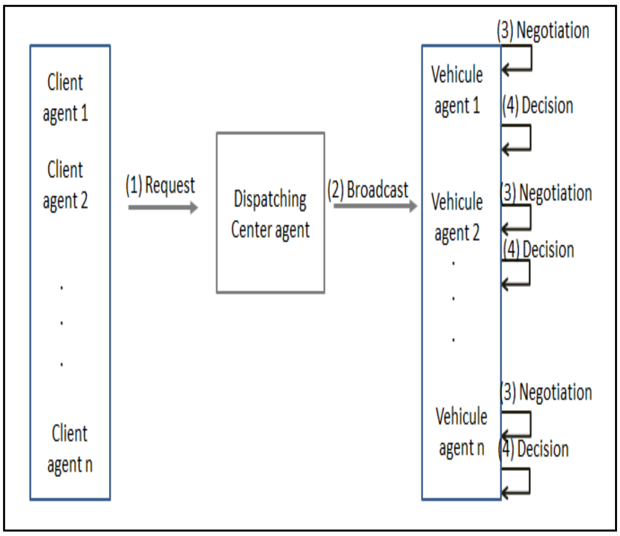

Figure 5. Dynamic Architecture TOD

Here we describe the messages exchanged between the passenger agent, the call center agent and the car agent.

1: Demand: the passenger sends a request to the call center in which it details its coordinates.

2: Broadcast: call center broadcasts the list of applications for all vehicles.

3: Negotiation: the vehicle will search for possible solutions to serve passengers and share them with other vehicles.

4: Decision: After negotiation, the vehicles take optimal decisions to satisfy the desires of passengers.

After the decision, the vehicles are confident that the action to be found is the best. Finally, the vehicle, responsible for transporting the passenger, informs the call center by this action.

5) Algorithm executed by the agent vehicle

The system we have invented is composed of several algorithms and modules, but the allocation of the right vehicles to passengers is the final and most complicated solution to achieve. Therefore, in Fig. 6 we show an overview of the algorithm executed by the agent vehicle, which is responsible for determining the correct solution.

Pseudo-code of genetic algorithm

Input: Evaluation function f, the maximum number of iterations n

Output: Best individual found

For (i=0; i<N && ! Stop condition; i++)

- Evaluate each individual in the population who satisfy the E function
- Select the parents in the population
- Produce children of parents selected by crossing
- Mutate individuals
- Expand the population by adding children
- Reduce the population

End For

Figure 6. Pseudo-code of the genitic algorithm

The “E” function, checks the constraint, that each vehicle must not pass the reached point of β_i before passing the starting point φ_i that the passenger “i” correspondent.

We have to satisfy these constraints for the evaluation:

$nb(\beta) = nb(\varphi) = 2$ in the chromosome.

$\forall \beta \in B$; Chromosome $[0] \neq \beta$.

$\forall \varphi \in F, \ \forall \beta \in B$;

Position (Chromosome $[\varphi_i]$) < Position (Chromosome $[\beta_i]$).

with

$i \in I=$ {passenger number}

$\varphi \in F=$ { point of departure }

$\beta \in B=$ {point of arrival}

III. Simulation and Results

In this section we describe the numerical results obtained after several tests on our system Stochastic TOD which is based on genetic algorithm named TOD-GA, and on the other TOD Stochastic system based on simulated annealing algorithm named TOD-SA which was used in 2011 by Zidi et al and modified by Issaoui et al on 2013 - i.e. see [15] and [5] -. This comparison is based on distance, time and success rate. The parameters of the genetic algorithm of the kind NSGAII are mentioned in the *Table 5*.

Seeing that the implementation of our approach on the dynamic DRP is not performed on real data, we simulate the operation of the transport system on demand. Indeed, we generate random requests distinguished by their location.

Our transportation system demand has "m" service vehicles average speed is 40 (km / h), which are available to "n" clients. The capacity of each car is equal to at most 2 for reasons of comfort. The time service call center can achieve successive 6 hours. Requests arrive in a random manner to the call center. Thereafter, the center sends these requests to the vehicles. These cars run the NSGAII algorithm and negotiate among themselves to determine the final solution based on stochastic constraints. This phenomenon is illustrated in the following figure Fig. 7.

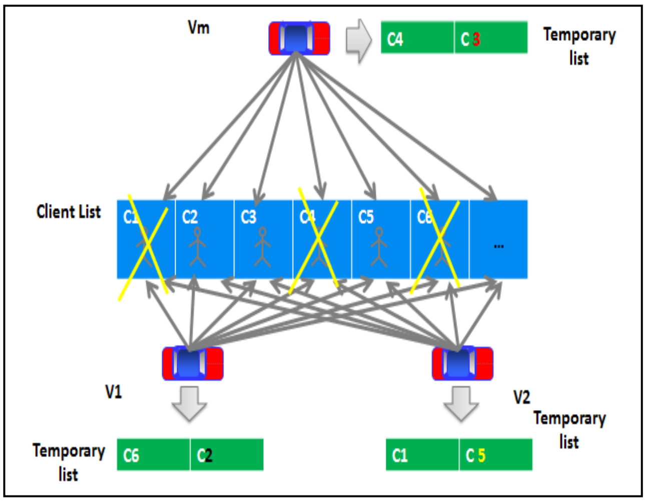

Figure 7. Assignment of the first passenger

Let the following list of customers [C1 ... Cn]. Customers have different coordinates (departure and arrival station). Vehicles, as a first step, tuck the first box of the Temporary list by the nearest customer. Thereafter, the vehicle will check these clients around the list. In a second step, they perform the NSGAII algorithm. In this example, the vehicles have concluded that the customers C2, C3 and C5 are the target customer to serve in the second. To guarantee the optimality of the final solution, vehicles will compare the results associated with each temporary list with respect to the distance traveled, the routing and the rate risk associated with this shuttle time. In the following figure Fig. 8, we clear up the situation.

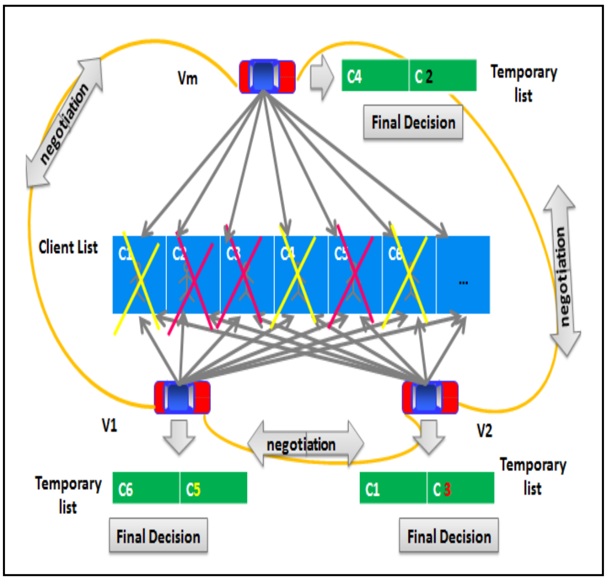

Figure 8. Assignment of the second passenger

After the negotiation made between V_1, V_2 and V_m car, the final solution is as follows:

V_1 car serves C_6 and C_5 customers, the vehicle V_2 serves C_1 and C_3 customers and V_m vehicle serves the C_4 and C_2 customers with total distance, total time and total rate risk well-determined and Optimal.

Table 5. The parameters of genetic algorithm

Parameters of GA	Values
Chromosome encoding	Real
Size chromosome	5
Population size	100
Number of generations	1000
Initialization population	Random
Technique selection	Ranking method
Crossing technique	2 points of cuts modified
Probability of crossing	P_{cross}= 0.65
Technology transfer	Reciprocal exchange
Probability of mutation	P_{mut}= 0.03
Insertion	Elitism
Stopping criterion	Maximum number of generations

The parameters of simulated annealing are: T0= 3000; α = 0.95 ; Tc = 0.001; NB-ITER-MAX= 1000. These values were chosen after several tests.

Before presenting the results of tests recall the two algorithms that we used to produce both TOD-GA and TOD-SA systems.

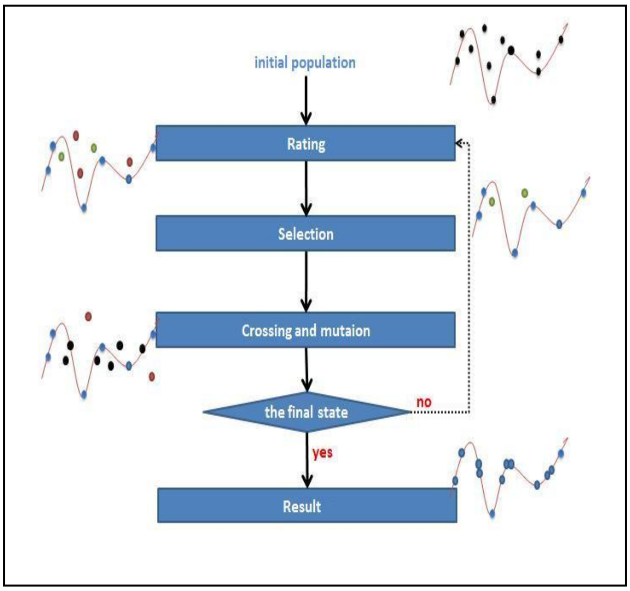

Figure 9. Genetic Algorithm

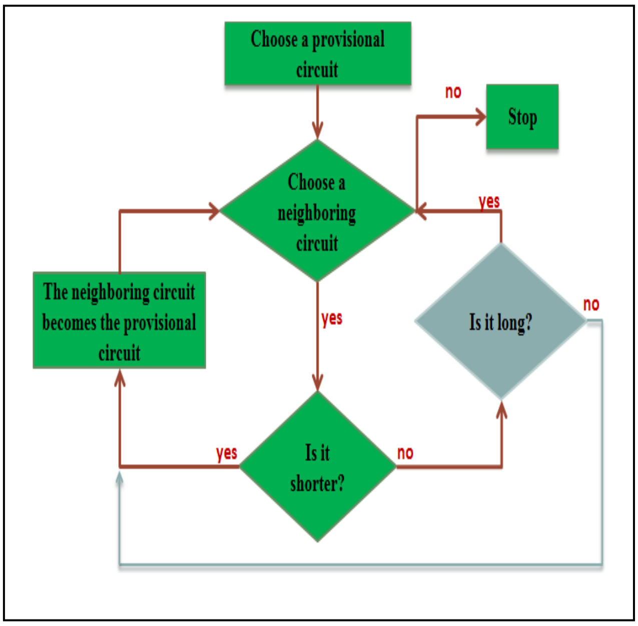

Figure 10. simulated Annealing Algorithm

1) Distances traveled

The distance remains a sensitive criterion to be optimized.

By examining the *Table 6* we derive two findings:

- The total distance traveled which is calculated by the system TOD-GA is lower than the TOD-SA system.

- The distances adopted by the TOD-GA system with 4 vehicles are also lower than the TOD-GA system with 2 vehicles.

Table 6. Representation of distances traveled

Nb clients	Test for 2 vehicles		Test for 4 vehicles	
	TOD-SA	TOD-GA	TOD-SA	TOD-GA
6	232	192	192	147
9	320	219	278	172
15	486	384	428	356
45	1361	1147	1347	1059
72	2022	1931	1977	1891
141	4274	3722	4213	3573
285	8972	7146	8955	6972
426	13401	11277	13364	11094
567	17519	14953	17448	14683
714	22046	17745	22197	17541
951	29328	21850	29281	21658
1089	33627	25328	33590	25107
1143	34650	26186	3417	26084

2) *Travel time*

Our second objective is the minimization of time racing vehicles (in Km). After running the two systems (TOD-GA and TOD-SA), we obtained values of time.

From results, shown in *Table 7*, it is clear that the TOD-GA system is better than the TOD-SA system in terms of time of transportation clients. In addition, the TOD-GA with 4 vehicles provides a service of TOD in a minimal time compared to TOD-GA with 2 vehicles.

Table 7. Representation of the travel time

Nb clients	Test for 2 vehicles		Test for 4 vehicles	
	TOD-SA	TOD-GA	TOD-SA	TOD-GA
6	6	5	5	4
9	8	5	7	4
15	12	10	11	9
45	34	29	34	26
72	51	48	49	47
141	107	93	105	89
285	224	179	224	174
426	335	281	334	277
567	437	374	436	367
714	551	444	555	439
951	733	546	732	541
1089	841	633	840	628
1143	866	655	865	652

.

3) *The rate of risk*

Rate of risk is a crucial criterion for our contribution. This value helps the TOD-GA and the TOD-SA system to choose the best solutions.

From *Table 8* after tests on both systems, we find that the TOD-GA is the best. But in general the comparison between the previous systems (at 2 and 4 vehicles) shows that the level of rate of risk increases when we increase the number of vehicles which is ordinary.

Table 8. Representation of the rate of risk

Nb clients	Test for 2 vehicles		Test for 4 vehicles	
	TOD-SA	TOD-GA	TOD-SA	TOD-GA
6	31	28	38	31
9	40	42	55	47
15	38	33	45	41
45	34	33	40	41
72	33	33	48	44
141	33	31	40	40
285	34	30	45	42
426	34	31	45	42
567	35	33	36	35
714	35	33	49	46
951	34	33	47	45
1089	35	39	47	42
1143	35	32	47	45

IV. Conclusion and perspectives

In this research, we developed a meta-heuristic based on NSGAII and a stochastic process using a MAS in order to resolve the Stochastic Dial a Ride Problem (SDRP). Solving this problem has an ecologic and economic impact. While transportation companies and passengers using transport can all benefit from this system of TOD. In fact, this system can improve the quality of service offered to users. Indeed, in case of congestion of public transport systems, they want to have reliable information and alternatives to make their travels.

In this research, we were able to identify prospects for future work. Indeed, we took in consideration the increase of service vehicles capacity. In other words, increasing the number of seats in the car from two to three or more seats. Secondly, we plan to serve another type of passengers such as handicapped passengers. And this requires another type of vehicles and depends on another study where other constraints considered exist. On the other hand, TOD-GA lasted more than 8 hours of execution and gave better results than its TOD-SA that lasted nearly 6 hours, because we worked in the dynamic context. So we aim to refine and to lighten the NSGAII in order to get closer to optimality in a reduced time. Later we will perform hybridization between our heuristic with Mixed Integer Linear Programming (MILP) or Integer Linear Programming (ILP) to be closer to the optimal solution.

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