A COOPERATIVE APPROACH BETWEEN GENETIC ALGORITHM AND TABU SEARCH FOR TRANSPORTATION NETWORK REGULATION

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ABSRACT: *This paper deals with the regulation of urban transportation system as an optimization problem. Our work is an extension of the evolutionary solution given in (Fayech, 2003). We propose a cooperative approach (AGTABU) between a Genetic Algorithm and a Tabu Search. AGTABU is firstly a genetic algorithm based on controlled operators. Moreover, every solution generated by genetic operations is improved by applying an adaptive Tabu search based on multiple movement operators. The selection of tabu search operators depends on the objective of the regulation problem. The present approach is applied to the public transportation system with a possible partial reconfiguration of the initial network. It provides to the regulator relevant decisions compared to non cooperative approaches.*

KEYWORDS: *Multimodal Transportation network, optimization problem, Genetic Algorithm, Tabu Search, Movement Operator.*

1. INTRODUCTION

Recently, the number of public transportation companies has been multiplied which increased competition in this domain. To ensure a good service quality level to customers, they have to find establish schedules that satisfy simultaneously two axis costs and the traffic management. The later axis consists on the minimization of the waiting time, the respect of departure and arrival time and the time of costumers' exchanges on the connection nodes. Due to incidents and random real phenomena (accidents, lack of materials…), it's hard to respect initial pre-established schedules. In this situation, the regulator has to undertake, immediately, the appropriate decisions (deceleration, changing stops…) that absorb traffic disturbances. The regulation process must consider regulator's task that is usually very difficult and complex. This complexity is due to the high number of information related to transportation network that must be collected and treated in real-time and the random aspect of real incidents. So, it's very interesting to help the regulator with a system that finds, evaluates and proposes realisable solutions.

Formulated as an optimization problem, the real-time regulation problem was demonstrated as a NP-hard one (Borne and al, 2003). Many algorithms were proposed to resolve it. In (Soulhi, 2000), the author has proposed a decision-support system with the contribution of artificial intelligence for the management of urban transport system. The work proposed by Laichour is based on a multi-agent approach to resolve only the problem of exchange nodes (Ould Sidi and al, 2005). In (Chihaib, 2002), a fuzzy system has been proposed to resolve the inter-stations disturbances. Lately, Fayech adopted a multi-agent approach (Fayech, 2003) which integrates a genetic algorithm to resolve multimodal transportation network regulation. In (Bouamrane and al, 2004), authors proposed a decision support system for the traffic regulation. The proposed decision model provides to regulator different regulation strategies to handle disturbances.

Most of the established approaches deal with the regulation in specific disturbed situations (exchange disturbances in nodes, inter-station disturbances …). Also, they do not consider all the possible regulation decisions. In our approach, in order to represent all the disturbed situations and regulation measures, we consider the problem itself as a rescheduling one. We will handle three regulation criteria to provide the regulator with eventually a reconfiguration network.

With the emergence of meta-heuristics, we propose in this work a new cooperative approach based on: Genetic Algorithm (GA) and Tabu Search (TS) to resolve the transport regulation problem. Recently, meta-heuristics (Genetic Algorithm (Goldberg, 1989), Tabu Search (Glover and Laguana, 1997), Simulated Annealing, and Ant Colonies have been successfully applied to various optimization problems (Dreo and al, 2003) (Collette and Siarry, 2002). In order to benefit from the advantages of meta-heuristics, the cooperation between different methods has been studied and different hybrid solutions have been proposed. In the last years, different schemes of cooperation were designed in order to standardize this research axis and to find a correspondence law between the cooperative scheme and the nature of problems (Basseur and al, 2003), (Bachelet and al, 1997).

In this paper, we present a cooperative approach applied to the multimodal transport regulation problem with a partial reconfiguration of the initial network. This problem is resolved as a multi-objective optimization one.

The organization of this paper is as follows. Section 2 presents the formulation of the transport regulation problem. In section 3, we explain the different steps of our algorithm AGTABU. We present the proposed genetic algorithm, and the adaptive tabu search operators that perform the different movements. In this section, we will discuss also cooperation mode between the two algorithms. Then we present the results obtained for the transport regulation problem in section 4. The effectiveness of the proposed cooperative approach is demonstrated comparing to genetic and tabu algorithm applied separately to the same problem. Section 5 concludes this paper.

2. PROBLEM FORMULATION

2.1. Space-time horizon

To control the evolution of the disturbances, we define the space-time horizon limits related to the search space (Fayech, 2003). This horizon determines the vehicles and stops concerned by the disturbance and the regulation decisions. The set of stops, S^H, describe the spatial axis of the problem and the set of vehicles, V^H, describe the time one. We suppose that this horizon is adapted to the real changing conditions of the network.

$$H = \left\{S^H \cup V^H\right\}. \quad (1)$$

So, V_i^l is the i-th vehicle of the line *l* and S_j^m is the j-th stop situated on the line *m* of the network. We suppose that a predefined diagnostic and analysis system determine the space-time horizon H and localize the disturbance. In this situation, our task is to palliate the disturbance, in real-time, by finding the appropriate decisions to undertake on each couple $\left(S_j^m \cup V_i^l\right) \in S^H \times V^H$.

In order to illustrate the possibility of the network reconfiguration, we consider the flexibility characteristics of the routes (Fayech, 2003). The flexibility parameter: $u\left(S_j^j V_i^l\right) = 0$ if the passage of V_i^l by S_j^m has to occur and it is equal to 1 if this passage can be cancelled.

2.2. Decision variables

The resolution of this problem consists on finding the new routes assigned to different vehicles and the passage times on each stop.

We consider the following decision variables (Fayech, 2003). The 0-1 passage variable determines new routes for each vehicle. We denote $a_{ij}^{lm} = 1$ if V_i^l stops at S_j^m and it is null otherwise. The destination variable x_{ijk}^{lmr} is 1 if V_i^l travels directly from S_j^m to S_k^r and null otherwise. We denote ta_{ij}^{lm} and td_{ij}^{lm} the arrival and the departure time of vehicle V_i^l at station S_j^m, respectively. Furthermore, we consider the 0-1 transfer variable $y_{ii'j}^{ll'm}$ which is equal to 1 if a connection between vehicles V_i^l and $V_{i'}^{l'}$ at stop S_j^m and null otherwise. In addition, we consider decision variable ε_{ij}^{lm}, representing decision to undertake on stop times. This variable defines the alteration of the initial stopping time of V_i^l at S_j^m. An acceleration or deceleration decision can be considered as a stop alteration on the next stop. According to initial routes, we construct for each vehicle V_i^l an affectation scheme (figure 1). This scheme is represented as an assignment graph composed by vehicle stops extended with two virtual stops: the departure (*d*) and arrival stop (*f*). Punctuated nodes illustrate stops which are flexible to be altered.

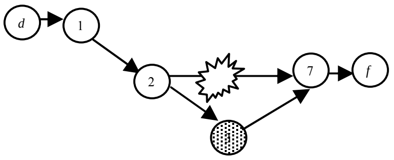

Figure 1: Example of assignment scheme of vehicle V_i^l

We are based on assignment schemes of vehicles and stop times to construct the solutions. This solution is determined by finding: first the new travelling routes of vehicles and second the stop time decisions modifications on each vehicle route. Illustrated by figure 2, the solution of a regulation problem can be considered as a parallel list of vehicles routes. Each vehicle route is composed by couples $(S_j^m, \varepsilon_{ij}^{lm})$ representing the stop and the decision of alteration of the initial stopping time, respectively.

V_1^l	*(d,0), (1,0), (2,0), (4,0), (6,2), (f,0)*
	(d,0), (1,0), (3,0), (5,3), (6,0), (7,0), (8,3), (f,0)
…	…
V_l^i	*(d,0), (1,0), (3,0), (5,3), (6,0), (7,1), (8,3), (f,0)*

Figure 2: Solution encoding of regulation problem

2.3. Regulation criteria

In this work, we were interested in minimizing three regulation criteria (Fayech, 2003). The first criterion consists on the regularity of the time intervals between the successive passages of the vehicles at the stop. It is related to the minimization of the waiting time (WT) on each stop for the different vehicles. The total waiting time of a vehicle is defined as follows:

$$WT = \sum_{S_j^m \in S} \times \sum_{V_i^l} a_{ij}^{lm} \times \sum_{S_k^r > S_j^m} \mu_{S_j^m} \times \frac{\Delta t^2}{2}$$

where $\Delta t = ta_{i'j}^{l'm} - td_{ij}^{lm}$ and $\mu_{S_j^m}$ is the constant arriving rate of the passengers at stop S_j^m.

The transfer time (TT) criterion is related to the transfer duration on all connecting nodes of the transportation network.

$$TT = \sum_{V_i^l} \sum_{V_{i'}^{l'}} \sum_{S_j^m} \left(y_{ii'j}^{ll'm} \times \omega_{ii'j}^{ll'm} \times \left(td_{i'j}^{l'm} - ta_{ij}^{lm} \right) \right)$$

with $\omega_{ii'j}^{ll'm}$ is the number of transferring passengers from vehicle V_i^l to vehicle $V_{i'}^{l'}$ at station S_j^m.

Finally, the route criterion deals with the duration of the total travelling time (RT). It is also named the punctuality criterion.

$$RT = \sum_V \sum_S a_{ij}^{lm} \times C_{il}^{j'm'} \times \left(td_{ij}^{lm} - ta_{ij'}^{lm'} \right)$$

with C_{ij}^{lm} is the load of V_i^l at its departure from S_j^m.

2.4. Objective function

One way to resolve a multiobjective optimization problem is the use of the Pareto optimality technique. This technique is based on dominance relation between solutions. It consists on finding non dominated solutions. The basic problem of this technique is the final decision and the selection of the global solutions of the problem. These solutions represent the front of Pareto.

In our problem, considered regulation criteria are antagonist and take values according to different scales (Fayech, 2003) which make the selection of global solution very difficult. To simplify the resolution, we propose the application of an aggregation technique which transforms the initial multiobjective problem into another problem defined by a unique objective function (2). This aggregation is defined by weights according to each criterion. A weight parameter represents a level of criterion importance that is determined by regulators. This parameter will be null if the regulator ignores the associated criterion.

The objective function represents the impact of the regulation decisions on the disturbed schedules. We define an objective function (fitness) of the solution x by the following weighted sum of the 3 criteria:

$$\textit{Maximize } f(x) = w_1 (WT_0 - WT) + w_2 (RT_0 - RT) + w_3 (TT_0 - TT) \, . \quad (2)$$

The Variables WT_0, TT_0, RT_0 represent the initial Waiting Time of passengers at the different stops, the initial Transfer Time between the different vehicles and the initial Route Time, respectively, in the disturbed situation without regulation. Parameters w_1, w_2, w_3 are nonnegative weight values for regularity, transfer and routing criteria respectively.

3. PROPOSED SOLUTION

3.1. Motivation and global scheme of AGTABU

Cooperation between Genetic Algorithm and local search is proved to be efficient to resolve optimization problem, they seem to be complementary (Fleurent and Ferland, 1994). In fact, the main problem of a local search is the interruption of iterative search when there is no improvement of the current solution. Usually, this iterative search deals with a local optimum but not necessarily the global optimum of an optimization problem. One way to escape from a trap of local optimality is to launch different executions with different initial points of the search space.

On the other hand, the evolution of genetic algorithm is usually threatened by the population uniformity which is characterized by a straight evolution (no individual amelioration, individuals with same genetic code). To escape from a uniform population, genetic operators must be controlled by a diversification method. Therefore, a sophisticated local search like a tabu search can play this role. In fact, the Tabu list prohibits already visited solutions which ensure the exploitation of new individuals.

The proposed solution AGTABU is a cooperation between a genetic algorithm and a tabu search. As shown in the following figure, AGTABU is based on a Parallel Synchronous Hybridization scheme (Bachelet and al, 1997). The Tabu search has the role of a sophisticated mutation using a memory containing a tabu list (Fleurent and Ferland, 1994) that can improve the genetic population. In fact, Tabu search is a local improvement of the individual not only a random modification. New solutions obtained by tabu movements can be rejected if found in the tabu list. By this manner, we exploit better the search space by inhibiting visited solutions.

The scheme of the present approach is in fact a general solution that can be applied to any optimization problem. In this work we restrict the application of AGTABU algorithm to a three-objective optimization problem. AGTABU is based on specific controlled operators that will be presented in the next paragraph.

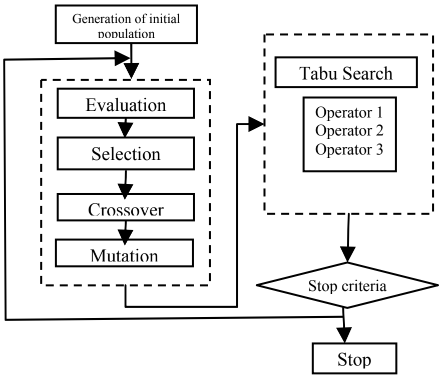

Figure 3: Global Scheme of AGTABU

3.2. Objective function homogenization

In the present problem, we have to optimize simultaneous heterogeneous objectives. In (Fayech, 2003), it has been shown that the different criteria: waiting time, transfer time and routing time have different variation scales. In fact, the travelling time weighted with vehicle loads is larger than the waiting time which is weighted by the number of waiting passengers at different stations. In order to minimize the influence of this difference in criteria domain, we propose to apply a homogenization approach to the initial objective function. So, the evaluation step, both in the genetic algorithm and the tabu search, will be more efficient and will generate more precise solutions. Hence, we propose to replace the initial objective function presented in paragraph 2.2. by the equivalent maximization one:

$$Maximize\ f(x) = w_1 \frac{WT_0 - WT}{f(x^*)} + w_2 \frac{RT_0 - RT}{f(x^*)} + w_3 \frac{TT_0 - TT}{f(x^*)}. \quad (3)$$

with x^* represents the best individual obtained in the current genetic population having the minimal criteria $WT_{\min}$, $TT_{\min}$ and $RT_{\min}$:

$$f(x^*) = w_1(WT_0 - WT_{\min}) + w_2(RT_0 - RT_{\min}) + w_3(TT_0 - TT_{\min}). \quad (4)$$

Unfortunately, for the transport regulation problem the lower bounds of the regulation criteria: regularity, transfer time, and routing time have not been demonstrated. In (Ould Sidi and al, 2005), the authors consider these lower bounds equal to the pre-established theoretical schedules, without transport perturbation. However, these values could not be used in our resolution. In fact, the reconfiguration characteristic of the initial transportation network can deal with values of WT, TT and RT that are better than the theoretical ones. We propose to set the variables $WT_{\min}$, $TT_{\min}$ and $RT_{\min}$ to the best values founded on the current population.

3.3. Genetic operators

We define controlled genetic operators. In fact, a two-point crossover operator is applied to individuals that generate feasible solutions by eliminating redundant nodes on vehicles routes.
Furthermore, we propose specific mutation operators. Two ways of mutation are proposed. The first one consists on the alteration of the decision variable ε_{ij}^{lm}.
The second mutation operation consists on the alteration of the passage decision of each vehicle route. For each initial vehicle itinerary, we search flexible stops that can be altered. This alteration can be elimination or insertion of one stop of the initial vehicle route.

3.4. Tabu search movements and criteria

The flexibility property of the network stops (Fayech, 2003) consists on defining stops that are flexible to be skipped or added to initial vehicle routes. Hence, vehicles can change their initial routes and generate new configurations of transportation network that are different from the initial one. This reconfiguration network characteristic allows using interesting movements that are generally used for the Vehicle Routing Problem (VRP) resolution (Dreo and al, 2003). We propose three movements to apply as Tabu search operators: permutation, insertion and elimination movement. These operators deal with both intra-routes and inter-routes exchanges in order to efficiently exploit space search. We randomly select one of these operators to apply to an initial solution to generate the neighbourhood. Furthermore, proposed movements are controlled and generate feasible solutions.

We studied also, the effect of the different movements on optimization criteria: what is the best movement that optimizes better the single criterion of regularity? The same question is related to the transfer and punctuality criterion. Thus, the multi-objective characteristic of our problem optimization can be moderated not only by weight parameters but also by tabu movements that can optimize one objective rather than another.

3.4.1 Permutation movement

This movement consists in determining the possible permutation between flexible stops to generate new routes for vehicles. This movement optimizes the transfer criterion. In fact, the permutation of stops in favour of exchange nodes guarantees the feasibility of transfer. We explain this movement by the following example.

For a given vehicle V_0^l of the transport line *l*, the following figure represents its assignment scheme.

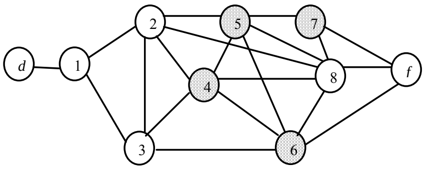

Figure 4. Assignment scheme for the vehicle 0

According to this scheme, we consider an initial travel route of vehicle V_0^l illustrated by the following table. This itinerary is presented by successive couples representing stations and stopping time.

Route 0	*(d,0), (1,0), (2,0),* ***(3,1), (4,3), (5,0)****, (8,0),* ***(6,0)****, (f,0)*

Table 1. Initial route for vehicle 0

The permutation movement is applied to the initial vehicle route to obtain a neighbourhood (table 2) with four possible routes. This neighbourhood is generated by simply modifying positions of flexible stops in the initial route. The assignment route to vehicle V_0^l is the one which maximizes the global fitness function.

Route 1	*(d,0), (1,0),* ***(3,0), (2,1)****, (4,0), (5,3), (8,0) , (6,0) , (f,0)*
Route 2	*(d,0), (1,0),(3,0), (2,1),* ***(5,3), (4,0)****, (8,0) , (6,0) , (f,0)*
Route 3	*(d,0), (1,0), (2,0), (3,1), (4,3), (8,0) , (5,0), (6,0) , (f,0)*
Route 4	*(d,0), (1,0), (2,0), (3,1), (4,3), (5,0),* ***(6,0) , (8,0)*** *, (f,0)*

Table 1. Neighborhood generated by the permutation movement applied on the route of vehicle V_0^l

3.4.2 Elimination movement

The initial vehicle route can be altered by eliminating one flexible stop. This operator can be efficient for transfer criterion if the vehicle must skip stops to accomplish important transfer with other vehicles. Therefore, this movement minimizes the waiting time of passenger; thus the total routing time will be optimized.

3.4.3 Insertion movement

In consequence of eventual accidents in the transportation network, some stops could not be served in time. In order to minimize the waiting time of passengers on these stations, we suggest adding the not served stops to initial routes of other vehicles. Therefore, these routes can be modified by the insertion of flexible stops and the search of the best new solution that optimizes the objective function. So, this movement can be efficient to optimize both regularity and transfer criteria.

3.5. Cooperation characteristics

The first step of AGTABU is the generation of a random initial population. We select then individuals that will be evolved through genetic operators. We apply the presented crossover and mutation to generate the new population. This population is improved by the TS.

The issue to be addressed to this cooperation is how to divide the available computation time between Tabu search and Genetic algorithm. Because of the iterative characteristic of the Tabu search, this last method will consume the whole execution time of AGTABU algorithm. Thus, applying a tabu search to each individual of genetic population will inhibit straight genetic evolution and limit the number of generations. In (Ishibuchi and Muruta, 1998), authors propose to apply iterative procedure to a sub-population of a genetic algorithm. So, we propose to select randomly a sub-population of *max_nb_indiv* individuals of the current population to be improved by a tabu search.

In the second step of AGTABU, we start with a current initial solution *current_solut* of the sub-population. The tabu list is initialized to the initial solution. We apply to this solution movements in order to generate the maximal number of neighbour *nb_max_vois*. Then, we select the best individual of the neighbourhood and maintain it in the Tabu list. This individual will replace the current solution *current_solut*. We repeat the search iteration of the TS starting with the new current solution. On each iteration, the tabu list is updated by incrementing its current size. The size of the tabu list is limited to a maximum value of the variable *size_tlist_max*. Finally, we select the best solution, denoted by *best_all*, in the tabu list as the result of the tabu search algorithm. This algorithm is stopped after a maximum number of iterations *nb_max_iter*, or after a successive number of iterations where it encounters the same prohibited solution. The *best_all* solution will replace the initial individual in the genetic algorithm. The AGTABU algorithm is stopped after a maximal number of iterations of the genetic evolution *nb_max_gen*.

In this algorithm, we face different parameters that have to be regulated. In fact, in addition to the genetic algorithm parameters (*nb_max_gen,* crossover and mutation probabilities) and the TS parameters (*nb_max_vois, size_tlist_max, nb_max_iter*), we have to regulate cooperation mode parameters especially the size *max_nb_indiv* of the subpopulation to be improved by the TS.

4. ILLUSTRATIVE EXAMPLES

In this section, we illustrate the proposed cooperative algorithm through an example of scenarios of perturbed transportation network.

The algorithm was implemented in Visual C++ 6.0 and the tests were run on o computer with Pentium IV CPU.

4.1. Scenario 1

This scenario was treated in (Fayech, 2003). We consider the two transport lines 5 and 7. The vehicle V_8^7 was confronted to a manifestation at station 9 of line 7 (Figure 5). The driver regards a delay of 7 minutes. This delay could cause the non feasibility of passenger transfer at transfer node 4. Through the supervision-support system, the regulator was informed and has to undertake efficient decisions to palliate this disturbance.

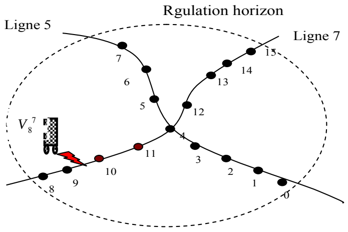

Figure 5: Scenario 1

The solution will be restricted to a set of vehicles and stations defining a regulation horizon. The execution of AGTABU determines vehicles' routes and alterations of the time stopping on each stop.

We have executed the algorithm for this scenario, through 7000 generations, modifying in each experiment weight parameters. We have tried to balance the total number of evolved solutions in the different algorithms GA and TS (population size=100, *max_nb_ind*=10, *nb_max_iter*=20, *nb_max_vois*=3).

We obtained the same solutions presented in (Fayech, 2003) and illustrated on table 4. For both algorithms, we have to maximize the difference between times in the theoretical and the disturbance situation.

(w_1, w_2, w_3)	AGTABU				AG			
	WT_0-WT	TT_0-TT	RT_0-RT	cost	WT_0-WT	TT_0-TT	RT_0-RT	cost
(0,0,1)	114	20	75	75	114	20	75	75
(0,1,0)	100	193	-5134	193	72	193	-4337	193
(1/3,1/3, 1/3)	230	130	-748	-129	114	158	-750	-159
(0.1, 0.85,0.05)	115	158	-1011	96	124	158	-1101	92

Table 2. Criteria values and costs obtained for AGTABU and AG

In order to demonstrate the relevance of the cooperative approach comparing to GA, we illustrate the evolution of these two algorithms separately. In this experiment, although algorithms reach one straight fitness value, the cooperative version converges faster than the genetic algorithm. This could be an interesting result when the regulator has to palliate perturbation in real-time and doesn't search the optimality.

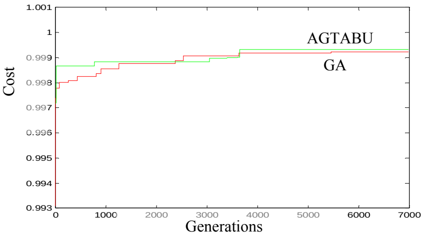

Figure 6: Evolution of AGTABU and GA

It is important to compare the execution durations of the different algorithms in millisecond. We are interested especially in the evolution of genetic and AGTABU algorithm. We have tested this scenario with the following parameters w_1=0.5, w_2=0.45, w_3=0.05. The following figure demonstrates that the AGTABU converges faster than GA.

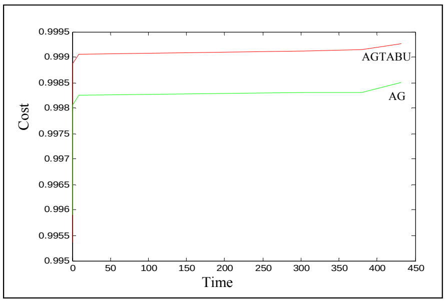

Figure 7 : Time evolution

4.2. Scenario 2

The objective of this scenario is to justify relations between regulation criteria and tabu movements. We consider two transport lines 1 and 2 having a common transfer node 4. The vehicle V_0^2 encounters route congestion at line 2. The driver was obliged to decelerate and declare to the regulator a delay of 5 minutes to arrive to the next station. The following figure presents the travelling graph of vehicle V_0^2. The punctuated nodes are flexible to be skipped or added at others routes.

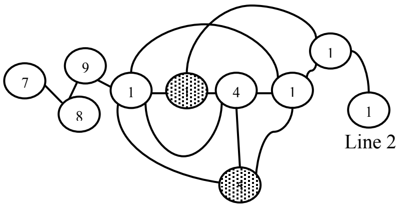

Figure 8: Travelling graph of vehicle V_0^2

We execute the AGTABU for this scenario in order to optimize the transfer criterion ($w_1 = 0, w_2 = 0, w_3 = 1$). We realize three experiments related to three movements (Permutation, insertion and elimination movement). The figure 9 shows that the algorithm based on a permutation movement converges faster than the others evolutions. This means that the permutation movement is more efficient than others movements in the optimization the transfer criterion.

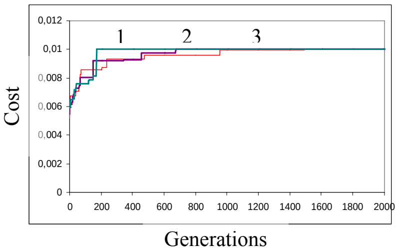

Figure 9: Algorithm evolution restricted to one criterion: transfer time (1: Permutation movement, 2: Insertion movement and 3: Elimination movement)

We apply the same procedure to the punctuality criterion ($(w_1 = 0, w_2 = 1, w_3 = 0)$). Three experiments related to the permutation, insertion and elimination movements were treated. The algorithm based on the elimination movement converges faster than others algorithms. In fact, less stops the routes contain, more the routing time is optimized. We have analyzed the regularity criterion using the same procedure; the evolutions of algorithms with permutation, insertion and elimination movements were similar. We suggest that a combination of three movements will be better to optimize regularity criterion.

5. CONCLUSION

In this paper, we proposed a multi-objective cooperative Genetic Tabu search algorithm to resolve the regulation of a multimodal transportation network problem. The proposed algorithm is an extension of the solution in (Fayech, 2003). In the proposed algorithm, the Tabu search is applied to a sub-population of the current population generated by genetic operations. We have proposed different movement operators to generate the neighbourhood for the tabu search. We have studied the effect of these operators to optimize separately the different regulation criteria (waiting time, transfer time, and routing time). Applied to different scenarios of disturbances in the transportation network, the performance of our algorithm AGTABU was demonstrated comparing to non cooperative algorithms: classical genetic algorithm and tabu search. Other future issues could be the construction of a fuzzy system that performs more the correspondence between regulator weight parameters and tabu movements.

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