A Co-modal Transport Information System in a Distributed Environment

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Abstract

This paper is aimed at presenting a transport information system that is dedicated to the co-modal transportation services. The problem is formulated with a three layers model and this work concentrates on the second layer — the assignment of the vehicles on each section of the itineraries. In terms of cost, travel time and other criteria, the optimization for choosing the best route for each request is implemented with Evolutionary Algorithms (EAs) and local search algorithm for the allocation of limited transportation resource. A special encoding method is developed to adapt the concerned problem and the operators for EAs are also detailed. With the aggregation approach, the fitness function is defined for EAs. According to the size of requests and the characteristics of the problem, an appropriate algorithm will be selected. With respect to users' preferences and availability of vehicles, the simulation is provided in this contribution to illustrate the proposed method.

Key Words

Assignment, co-modal transport, distributed network, EAs, optimization.
I. INTRODUCTION

For the economical and environmental reasons, some new modes of transportation emerge and get more and more popular in recent years, like the carpooling (e.g., http://www.covoiturage.fr) and free-use car (e.g., AutoLib in Paris). In 2006, the European commission introduced a new concept: co-modality [1] that refers to a use of different modes on their own and in combination in seeking for the aim of an optimal and sustainable utilization of resources. With this notion, it means finding an optimum searching in the relevant domain of the various transports (including individual and public transport) and of their combination, in a way where travel cost, traveling time, distance, environment impact, comfort conditions, quality of service etc. are taken into account. In a co-modal transport information system, travel information about various transportation, like the best routing and schedule in the above optimum way is provided to the users. Its decentralized features of its data characterize a distributed information system. Generally, only the subsystems take full control of their own data. When necessary, the detailed information about one route such as the schedule and the availability of the cars will be demanded through networks, and meanwhile, the subsystems offer their local information. One entire journey may involve several transport operators, then different subsystems. The main system is in charge of finding out the global information throughout the subsystems that process the local information. The distributed information system avoids the maintenance and updating of the data from each information provider, and for the privacies reasons for the companies, it’s more acceptable. Essentially, the departure spot, the destination spot and the related time are indispensable to launch an itinerary query. For advanced options, constrains like the preference of transportation tools and the flexible time window allow the system to return more suitable itineraries. The agent computing paradigm is rapidly emerging as one of the powerful technologies for the development of large-scale distributed systems to deal with the uncertainty in a dynamic environment due to its autonomous, reactive and proactive nature [2] [3]. In this dynamic problem, the subsystems are independent from each other, and the member routes will interact together to formulate a complete itinerary, under the communication protocol. The goal of the paper is to describe a new approach to resolve the time-dependent co-modal problem in the distributed transportation networks. Along with the mathematical notions, some scenarios of simulation are also presented to verify its efficiency. The reminder of this paper is structured as follows: Section II contains research overview, where the state of art in the multi-modal transport, distributed environment transport optimization is emphasized. In Section III, the advantages and the main features are given. In section IV, with the formulation of the problem in a mathematical way, the solution to the problem and the relevant model are described. Section V presents the configurations of performed experiences and the obtained simulation results. In the last Section, conclusions and future works will be presented.

II. RESEARCH OVERVIEW

Based on the graph theory, Dijkstra’s algorithm for the shortest route is the most used method, and lots of variant approaches [4] were developed for different problems and better computation performance. In [5], the research focused on the finding shortest path in urban multimodal transportations networks and minimizing the cost, time and other discommodity related to the paths. A utility function using the aggregation method considers the arcs cost and time weight in
the meantime the preference of the users associated with all the possible transportation modalities. Specifically, a purely theoretical proposal of possible values for the weighting coefficients is presented, especially the ones about the time and cost. Parameters should be well identified in order to precisely present how these factors affect users’ choices. In [6], Wang and Kampke introduced an algorithm for computing the shortest route in a distributed system during polynomial time. In a distributed system, there are several autonomous subsystems and a central computing center. The subsystems maintain and take full control of their own databases and provide the central computing server with the intersection information for transfers among themselves. In [7], an approach about identifying the fastest itinerary in a time-dependent distributed environment is presented. All the transportation vehicles are well scheduled in the subsystems. The central computer uses the transfer information and the incomplete local information provided by the independent subsystems to search the fastest itinerary from one spot to another across the subsystems. In [8], the research focused on the dynamic carpooling problem in a distributed transportation network.

Despite the great efforts made in this field, the complexity of the time-dependent co-modal transport problems has not been completely addressed. Our work mainly focus on the finding of the appropriate route for the users in condition that the resource like the availability of carpooling, the number of free-use cars are limited and that the cost and time constrains are imposed by the users. The genetic algorithm and the local search algorithm will switch automatically for a better performance. A completed itinerary can be composed of several routes, and there must be transfers between different transport operators. After the possible routes are identified, a process to form an entire itinerary from the departure spot to the arrival spot is executed. A protocol for the negotiation between the agents is also necessary to establish.

III. System Aims and Methodology

The goal of the system is to establish a co-modal transportation information system with which the demanded itineraries will be optimized with respect to the criterions and the preferences of the demanders and will be returned within a reasonable limit of time in case of immense quantity of quests. For the optimization process with EAs, a special encoding method is adopted. The optimization that is also a multi-criterion problem will be executed with the aggregation method for the fitness assignment function.

A. The Co-modal Transportation Network

In a multimodal transportation, an origin-destination path is composed of several sections (or routes) and each of them is ensured by one modality (car, train etc.), instead, in a co-modal transportation system, a section in one origin-destination path may be served by more than one modality where both public and private ones are considered. And these modalities compete with each other. After having received the requests from users, the system will find the most suitable modality from each section and then formulate a full path.
Let $G = (V, E, M)$ denote a directed transportation network, where $V = (v_1, ..., v_i)$ is the set of nodes representing the relevant spots, $M = (m_1, ..., m_j)$ is the set of transportation modalities (e.g., train, subway, car pooling and free-use car) [9] and $E = (e_1, ..., e_k)$ is the set of the directed arc (also called segment). A segment $e_k \in E$ connecting two nodes $v_p$ and $v_q$ can be determined using $(v_p, v_q)_{m_j}$ where $m_j \in M$ represents the relevant transportation modality.

Definition (Multimodal path [9]): In a given multimodal graph $G = (V, E, M)$, a multimodal path $(v_1, v_i)$ is a sequence of edges between a pair of nodes $v_1$ and $v_i$, the segments between these two nodes are represented by $((v_1, v_2)_{m_1}, ..., (v_{i-1}, v_i)_{m_{i-1}})$, where $\forall i, j \in [1, ..., k], v_i, v_j \in V, (v_i, v_{i+1})_{m_i} \in E, m_i \in M,$ and $i \neq j \iff v_i \neq v_j$.

Definition (Co-modal path [10][11]): In a given directed graph $G = (V, E, M)$, a co-modal path $(v_1, v_i)$ is a sequence of edges between a pair of nodes $v_1$ and $v_i$, the segments between these two nodes are represented by $\{(v_j, v_k)_{m_1, ..., m_l}\}$, where $((v_j, v_k)_{m_1, ..., m_l})$ means that the segment $(v_j \rightarrow v_k)$ can be ensured by any one mode in $\{m_1, ..., m_l\}$. In this paper, the following transportation modalities will be considered in the co-modal transportation network:

- Public modality (e.g., bus, metro, train): for the public transportation modalities, the departure and arrival time are usually predefined and the places available are considered as being enough. In the system, we take these characteristics into account.
- Carpooling: the departure and arrival time are usually predefined and may be changed anytime before departure, the most important factor is the available places; another characteristic is that one traveler can only take a partial itinerary.
- Free-use car: this modality is specially described by the number of available vehicles at the departure spot, besides, the cost of the travel composes of the service subscription fee and the use fee.

B. The Three Layers Model

In this part, a three layers model of the proposed solution for the co-modal transportation problem will be presented. From the users’ itineraries requests, the global optimal itineraries will be obtained [6] [7]. Each itinerary composes of one or more segments that are not necessarily ensured by the same transport operator and the transportation tools. The itineraries may also have segments in common, so the travelers share the segment of the route. In particular, the resource (e.g., carpooling) is limited. To get better allocation of the available resource and to well arrange the travelers’ journeys according to their preferences, a three layers model is implemented. Figure 1 is the proposed three layers model.

The first layer is served as the interface and the identification of global itineraries. The identified itineraries will be decomposed according to the areas, the transport operators and the service modalities. Thus, the decomposed segments and the demanded itineraries will be sent to the second layer and the third layer. In the second layer, the assignment for each traveller will be accomplished in the limit of available source of transportation service and the travelers’ preference. In the second layer, the modality will be chosen for each traveller in each segment. At
last, the assigned segments and the demanded itineraries permit a coalition among the routes to formulate the entire journey. The third layer is the last step to form a whole itinerary from the allocation agents gotten in the second layer. This step will be on the basis of some interaction protocol. The process of getting the segments allied is named in this paper combination of the segments. By the way, each layer contains a process of optimization.

Figure 2 is the entire activity diagram of this information system. The last part that is marked grey is to be worked on in the future. We will first study on the identification of the entire itineraries and the sections along with the possible service that ensures the transportation. The coalition (combination) of the identified sections will be a part of future work.

IV. PROPOSED APPROACH

In the dedicated transport information system, the work consists of three steps. First step, it’s to find the complete itinerary in the distributed environment to the requests. Second step, the itinerary found in the last step is probably composed of several segments of route, and services are provided by different operators, at the same time some of them have alternatives, for example, train, carpooling and free-use car are available to travel from one place to another during the entire journey. In this step, the system will find the optimized distribution transport tools for each traveller in condition that the resource like free-use cars is limited. The third step is to choose and to combine the optimized segments into a complete itinerary with the users constraints and preferences being taken into account.

The topic of this paper is to treat the problem of the second layer of the three layers model. After having gotten the global itineraries in the preceding step, to allocate the available vehicles with respect to the users’ preferences in each segment in a co-modal transportation network is the next step to carry out.
In the first step to find the shortest path in a distributed environment, we use the following approach. The use of transfer graph [9] and the approach proposed by [6] allows a rapid computation of a shortest path in a distributed system. Here, we will present the major steps rather than the details of the algorithms. Each operator of transportation is treated as an individual system and the graph that represents its network is individual. There is no central computing server to store the data and the problem becomes to find out the shortest path in the inter-class route graph. The Dijkstra’s is always the core algorithm for the “shortest path”.

A. Mathematical Formulation of the Problem

The problem is defined in the mathematical way as follows:

- At a time $t$, there are $N$ quasi-simultaneous requests for itineraries during a little interval of time $dt$. Use $R(t)$ to indicate the set of requests.
- In the distributed co-modal transportation network, $I(t)$ will be returned as the global optimal itineraries for the requests in $R(t)$.
- $\forall i \in \{1,2,\ldots,N\}$, there are $I(t)_i \in I(t), I(t)_i = \{S(t)_{i1},\ldots,S(t)_{iM}\}$ where $S(t)_{i1},\ldots,S(t)_{iM}$ are segments of $I(t)_i$.
- At the same time, there are segments shared by several itineraries. Let us take $S(t)_{im}$ as an example to study. Suppose that the segment $S(t)_{im}$ is shared by $K$ paths in the time window $[t_d,t_a]$ noted as $T$.
- To assure the segment $S(t)_{im}$, in the corresponding time window $S(t)_{im}$, there are $Q_1$ places available for car-pooling $M_c$, $Q_2$ available free-use cars $M_a$, and public transport $M_p$ that is considered with unlimited places for travelers.

B. The Assignment of the Vehicles

An efficient representation method is employed for the suitable adaptation to the problem. For each segment of the itinerary, we use the following method to indicate the transport modality that the traveler will engage.

We use the matrix for the assignment. In the following, we will explain how this works. For each element of the matrix, it represents the assignment of a user to one transportation tool or one vehicle. Each specific segment is represented by one matrix. The rows of the matrix correspond to the requests demanders whose itineraries may contain this route and the columns are related to the vehicles that ensure the service on this segment. With $S(t)_{im}$ referring to the route, $P$ referring to one traveller on route $S(t)_{im}$ and $V$ referring to one vehicle that ensures service on the segment $S(t)_{im}$, $CH$ denotes to the name of this assignment matrix, $C_p$ is the row index and $C_h$ is the column index, the element of the matrix is the assignment of the traveller in the following way:

$$CH[C_p,C_h](S(t)_{im}) = \begin{cases} 1, & \text{if } P \text{ is assigned to } V \\ *, & \text{if } P \text{ can be assigned to } V \\ 0, & \text{if } P \text{ can't be assigned to } V \end{cases}$$ (1)
Then, with this method of representation, we will get a matrix of assignment where the columns are the vehicles and the rows are the travelers. As a result, each element of the matrix indicates the assignment relation between the traveler and the vehicle. There are in total three different cases: firstly, the element “1” means that the traveler \( P \) will be assigned to the vehicle \( V \); secondly, the element “∗” in the matrix means that the traveler \( P \) may take the vehicle \( V \) as one of his options; at last, the element “0” implies the impossibility for the traveler \( P \) to take the vehicle \( V \).

So, the size of the matrix, which means the number of the potential travelers on this route as the rows, the number of the vehicles ensuring the service in the same time window as the columns, depends on the requests received by the transport information system simultaneously. It is impossible that a traveller takes more than one transportation tool on the same route without transfer, so he can be assigned to only one vehicle. In the case that some modalities are excluded in the travellers’ preference, the assignment to the relevant vehicles will not occur.

C. Evolutionary Approach

The problem can be treated as an allocation problem in which the limited transportation resource is allocated to the travelers. Some criteria like time and cost will be followed to get the allocation optimized and the travelers’ preferences will be respected. We propose an evolutionary algorithm to accomplish this optimization process. This assignment problem is a combinatorial multi-objective problem. The meta-heuristics are often used to solve this type of multi-objective combinatorial optimization problem [12][13]. For this problem, we choose an evolutionary approach.

In the first step of an evolutionary algorithm, it is necessary to establish an encoding method with which the chromosomes are formulated. An efficient encoding method is adopted for the suitable adaptation to the problem. With this encoding, the chromosome is in the form of matrix. To obtain the optimal assignment matrix for the route in terms of travel cost, travel time, travelers’ preference etc., an evolutionary approach is implemented. According to its characteristics, the problem transforms into a combinatorial optimization problem. As the sections of route are different from each other, we choose some indicators to describe the sections. In other words, the indicators are called attributes of the route that allow us to execute the optimization process. Traveling with a certain transportation tool in one route, the price paid is the travel cost and the time spent is the travel time. There are also others attributes like total gas emission, comfort conditions etc. To take several criteria into account for the optimization makes the problem become a multi-criterion and multi-objective problem.

Let us consider a multi-objective optimization problem with \( n \) objectives:

\[
\text{Maximize } f_1(x), f_2(x), \ldots, f_n(x)
\]

where \( f_1(\cdot), f_2(\cdot), \ldots, f_n(\cdot) \) are \( n \) objectives to be minimized.

When the following inequalities hold between two solutions \( x \) and \( y \), the solution \( y \) is said to dominate the solution \( x \):
If a solution is not dominated by any other solutions of the multi-objective optimization problem, this solution is said to be a non-dominated solution.

Let $M$ be a feasible assignment matrix for a section of path. A feasible assignment matrix $M^*$ for a multi-objective optimization problem, say optimize $x = (x_1, x_2, ..., x_p)$ is a non-dominated (Pareto) solution if there is none feasible assignment matrix $M$ such that $x_k(M)$ improves $x_k(M^*)$, $k \in \{1, 2, ..., p\}$, and $\exists m \in \{1, 2, ..., p\}, x_m(M) \neq x_m(M^*)$. For a $p$ objectives assignment optimization problem, the number of feasible solutions may grow exponentially with the number of users [5].

To avoid the difficulty of the multiplicity of Pareto optimal solutions, a utility function is proposed. In the evolutionary approach, the utility function is taken as the fitness function to be maximized/minimized and it is a function about the variables with which the results evolve. And it is possible and necessary to make homogeneous the different variables that will influence the user’s decision. For each modality of one section of the route, the variables like travel cost, travel time etc. are referred as the attributes of the route.

It is usually assumed that the fitness is a linear function of the attributes of the route [5], that is $f(x_1, x_2, ..., x_p) = \sum_{i=1}^{p} \beta_i x_i$, where $x_k$ is the value of the $k$th attribute and $\beta_k$ is the coefficient of $x_k$. It exists other similar forms of fitness function that will be discussed later.

Note that, for one segment $S(t)_{im}$, which is represented by an arc in the graph, its attributes like cost and time will be expressed in the fitness function. Apart from these involved attributes, the issues about the homogenization and the ratio between the coefficients should be considered.

When the EAs are applied to the multi-objective optimization problem, a fitness value of each solution should be evaluated. The fitness function of the solution $x$ can be defined by the following weighted sum of the $n$ objectives:

$$f(x) = \omega_1 f_1(x) + \omega_2 f_2(x) + \cdots + \omega_n f_n(x)$$  \hspace{1cm} (2)

where $\omega_1, \omega_2, ..., \omega_n$ are nonnegative weights for the $n$ objectives, which satisfy the following conditions:

$$\forall i \in \{1, 2, ..., n\}, \omega_i \geq 0 \text{ and } \sum_{i=1}^{n} \omega_i = 1$$

Each objective can be any function of the solution $x$. In our case we take $f_i(x) = v_i / x_i$ with the search direction weight vector $w^b = (\omega_1, \omega_2, ..., \omega_n)$.

Then the fitness function is transformed to the following form:

$$f(x) = \omega_1 v_1 / x_1 + \omega_2 v_2 / x_2 + \cdots + \omega_n v_n / x_n$$  \hspace{1cm} (3)
where the constants that make the different objectives homogeneous. Here, we take the solution related to the objective function .

The coefficients are used for weighting the different parameters in a way how they are perceived by the travelers. Without loss of the generality, we assume that the fitness function is to be minimized to get the optimal solution. In other words, the satisfaction of the traveler increases as the value of attribute increases.

The steps involved in this evolutionary algorithm for the vehicles assignment problem are as follows:

1. Generate an initial population of randomly constructed solutions. Each of the initial solutions is generated in a random way. Since initial solutions may violate the vehicles' capacity constrains, they may be infeasible.
2. A fitness function is defined with the method of aggregation.
3. Decode the solution structure. The assignment of the travelers to the vehicles in one route is represented in form of matrix. The fitness of each solution is calculated according to the fitness function defined before. Apart from the aggregation technique for the variables, it must take into account the degree of infeasibility that is a frequent approach in EAs. In evolutionary computation most of the constraint-handling methods are based on the concept of penalty functions [14]. In this case, when the assignment solution exceeds the number of available vehicles or vehicles' capacity, a penalty will be imposed on the fitness.
4. Select two parent matrices in the parent generation for reproduction. A roulette wheel selection method is adopted. On the roulette wheel each individual is represented by a space that proportionally corresponds to its fitness [15]. In a roulette wheel selection, the fittest individuals have a greater chance of survival than weaker ones. The fitter individuals will tend to have a better probability of survival and will go forward to from the mating pool for the next generation. To preserve the diversity, the weaker ones are not without chance because they may have genetic coding that proves useful to future generations.
5. Generate a child solution by applying firstly a crossover operator (combination) to the selected parents. The one-point crossover is chosen for this procedure in which a point for the crossover is selected randomly and the offspring solution will make up of the first part from the first parent and the second part taken from the other parent, or vice versa with equal probability. Globally, the crossover operator occurs with a certain probability. After the crossover operator, a mutation operation follows. In this procedure, it involves a mutation in a randomly selected gene, with a certain probability. Then the procedure of the correction of the mutation is executed to verify if the generated children are legal, which means that the constrains are satisfied. If not, the children chromosomes will be slightly modified.
6. Replace the individuals in the population by the child solutions, and then the offspring generation is obtained.
7. Repeat steps 4-6 until the best solution cannot be improved any more.

After selection step has been carried out, another population that is referred as intermediate
population in [15] is completely constructed, and then the crossover can occur. This crossover operator is applied to randomly paired chromosomes denoted \( P_c \). These chromosomes are recombined to two new matrixes with a probability \( P_c \).

Consider the following chromosomes Parent 1 and Parent 2:

<table>
<thead>
<tr>
<th>Parent 1</th>
<th>Parent 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R(x,y) )</td>
<td>( V_1 )</td>
</tr>
<tr>
<td>( P_1 )</td>
<td>0</td>
</tr>
<tr>
<td>( P_2 )</td>
<td>1</td>
</tr>
<tr>
<td>( P_3 )</td>
<td>*</td>
</tr>
<tr>
<td>( P_4 )</td>
<td>0</td>
</tr>
</tbody>
</table>

These two matrixes represent two possible solutions to the affection problem. Then using a single randomly chosen crossover point, the one-point operator takes place. Two offsprings are obtained in swapping the fragments between the two parents.

<table>
<thead>
<tr>
<th>Offspring 1</th>
<th>Offspring 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R(x,y) )</td>
<td>( V_1 )</td>
</tr>
<tr>
<td>( P_1 )</td>
<td>0</td>
</tr>
<tr>
<td>( P_2 )</td>
<td>1</td>
</tr>
<tr>
<td>( P_3 )</td>
<td>1</td>
</tr>
<tr>
<td>( P_4 )</td>
<td>0</td>
</tr>
</tbody>
</table>

The mutation operator follows the recombination procedure. For each bit in the population, mutate with a certain low probability \( P_m \). The following example will illustrate how this operator works.

After the mutation, some chromosome may become inappropriate for that the number of the passengers may exceed the capacity of the vehicle. In this case, the relevant affection should be modified with the vehicle’s volume and the user’s preference.

**D. An Alternative Optimization Approach**

The time of execution depends on the complexity of the algorithm and the size of the problem. To obtain a better performance of calculation, an optimization approach for this problem is proposed in case that the size of the requests at the same time is very limited and there is no need to launch EAs. At a time the requests are launched, the system will choose the appropriate algorithm.

The local search algorithm is one algorithm frequently used in the filed of scheduling. The
preferences of the users and the availability of the transportation tools are the only elements to consider. Briefly, the principle rule is “first arrived, first served”. The users are ranked in a certain order when they launch their itinerary queries. On the basis of this ranking the allocation is performed. With this algorithm, the vehicles will be allocated to the users according to their choices. The first choice is satisfied if the relevant vehicles are available; if not, the second choice will be considered, and so forth. The demanders’ preferences will be satisfied as much as possible.

E. Switching between algorithms

For the sake of performance and response time, the algorithms will be chosen automatically. The criterion to follow is the size of the problem and the availability of the resource to allocate. In the default case, the evolutionary algorithm is used; otherwise, when the quantity of requests is too limited to take full advantage of EAs or even the resource is too limited, the alternative approach will be chosen.

V. Simulation Results

In order to illustrate how the system works and to evaluate the approach proposed in this paper, a simulation example of requests will be presented as follows. In the simulations, here are the parameters for EAs:

- Population size: \( N_p = 100 \)
- Number of generations: \( N_g = 100 \)
- Mutation probability: \( P_m = 0.05 \)
- Crossover probability: \( P_c = 0.80 \)

As showed in Figure 3, there are 6 itineraries requests for the correspondent time window and we have gotten the shortest itinerary for each request. Here are the requests, \( I(t_0) = \{I(t_0)_1, I(t_0)_2, I(t_0)_3, I(t_0)_4, I(t_0)_5, I(t_0)_6\} \).

- \( I(t_0)_1 = A \rightarrow O[t_A,t_0] \); without preference;
- \( I(t_0)_2 = B \rightarrow K[t_B,t_K] \); no free-use car;
- \( I(t_0)_3 = C \rightarrow J[t_C,t_J] \); carpooling first;
- \( I(t_0)_4 = D \rightarrow N[t_D,t_N] \); free-use car first;
- \( I(t_0)_5 = E \rightarrow L[t_E,t_L] \); no carpooling;
- \( I(t_0)_6 = F \rightarrow M[t_F,t_M] \); no public transport.

After having identified the requests, we decompose the itineraries according to the geographical elements and the transportation modes. Thus, there are three areas and three general types of transportation in the decomposition, as showed in Figure 4.
In total, five transportation service providers are concerned across the transportation network, we name $C_1$ for public transportation in area I, $C_2$ for public transportation in area II, $C_3$ for public transportation in area III, $C_4$ for carpooling service and $C_5$ for free-use car service. Therefore the itineraries can be described in the following form: where $m_1$ represents public transport, $m_2$ and $m_3$ represent carpooling and free-use car, respectively.

$$I(t_0)_1 = \{((A,G)_{m_1,m_2,m_3},(G,H)_{m_1,m_2,m_3},(H,O)_{m_1,m_2,m_3})$$

$$I(t_0)_2 = \{((B,G)_{m_1,m_2,m_3},(G,H)_{m_1,m_2,m_3},(H,K)_{m_1,m_2,m_3})$$

$$I(t_0)_3 = \{(C,G)_{m_1,m_2,m_3},(G,H)_{m_1,m_2,m_3},(H,J)_{m_1,m_2,m_3}\}$$

$$I(t_0)_4 = \{(D,G)_{m_1,m_2,m_3},(G,H)_{m_1,m_2,m_3},(H,K)_{m_1,m_2,m_3}\}$$

$$I(t_0)_5 = \{(E,G)_{m_2,m_3},(G,H)_{m_1,m_2,m_3},(H,L)_{m_1}\}$$

$$I(t_0)_6 = \{(F,I)_{m_2},(I,H)_{m_2},(H,N)_{m_1,m_3}\}$$

There are several route segments, $(A,G),(D,G),(E,G),(F,G),(G,H),(H,J),(H,K),(H,L),(H,K)$, etc. which are assured by more than one transportation service. The segments $G,H$ are shared by several itineraries; thus, the assignment process will be launched to allocate the resource. As is showed in the graph, it’s in a distributed environment. The transportation service is provided by several operators. After the decomposition of the itineraries, the assignment will occur for each individual segment. In the following paragraphs, two examples will be presented to illustrate how the assignment works. For the common segment $(G,H)$ for the requests $I(t_0)_1,I(t_0)_2,I(t_0)_3,I(t_0)_4,I(t_0)_5$, the EAs will be applied for the assignment. We note the relevant time window is $T_0$. For the segment, $(H,N)$ for the request $I(t_0)_6$, the local search algorithm takes in charge of the assignment.

In this simulation, three parameters will be taken into account as optimization criterions. The travel cost, the traveling time and the comfort satisfaction for each segment are considered. As mentioned in section IV for the fitness function in EAs, the parameters will be homogenized so that they can be added. Also the weight that the parameter presents in the fitness function is a multiplication coefficient and is predefined. Take one route from G to H during the specified time window $T$ as example. The characteristics for each proposed transportation tools are shown in Table 1.

**Table 1: Characteristics of Different Transportation Tools From G to H During T**

<table>
<thead>
<tr>
<th>$R_f(D,L)$</th>
<th>Train</th>
<th>Carpooling</th>
<th>Free-use car</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (euros)</td>
<td>35</td>
<td>18</td>
<td>30</td>
</tr>
<tr>
<td>Time (mins)</td>
<td>70</td>
<td>120</td>
<td>90</td>
</tr>
<tr>
<td>Comfort</td>
<td>2</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

Here, we introduce a characteristic of the transportation tools: the comfort. It is the index of personal feeling of the user when using this method of transport. It varies from “1” to “5”, meanwhile “1” means the most comfortable and “5” means the least comfortable.

There are 5 transport demands for $(G,H)$ are 2 carpooling places and 1 free-use car. According to the definition in section IV and the data in Table 1, the fitness function is:

$$f(x) = \omega_1 v_1/x_1 + \omega_2 v_2/x_2 + \omega_3 v_3/x_3$$  \hspace{1cm} (4)

where $v_1 = 18, v_2 = 70, v_3 = 1$, $x_1$ is the cost, $x_2$ is the time, $x_3$ is the comfort level. For the weight vector of the fitness function, we have $\omega = (0.5, 0.3, 0.2)$. Thus, the weight parameters for the fitness function are as follows: travel cost $\omega_1 = 0.5$, travel time $\omega_2 = 0.3$ and comfort condition $\omega_3 = 0.2$. The fitness function becomes:
After the assignment with the EAs, a possible assignment matrix is obtained as the Table. It's possible that it exists more than one feasible solution; in this case our future work for the coalition of the segments will concentrate on choosing the best one. After the assignment process for each route, the following result for each request is gotten for each request. After the assignment with the EAs, a possible assignment matrix is obtained as the Table. It's possible that it exists more than one feasible solution; in this case our future work for the coalition of the segments will concentrate on choosing the best one. After the assignment process for each route, the following result for each request is gotten for each request.

Another simulation example is proposed in the local transportation network of Lille. The transportation flux is sometimes not avoidable. A strong demand of transport from near cities to Lille is also a problem. For the transportation between these cities, as in Figure 5, apart from private cars, there are regional train (Ter), free-use car and carpooling. At the same time, the carpooling can take passengers to the destination (Grand Stade), the free-use cars should be returned to the service center. The cost and the time needed for these transportation methods are as the following Table 2.

Table II: Characteristics of Different Transportation Tools From Dunkerque to Lille in T

<table>
<thead>
<tr>
<th>$R_T (D, L)$</th>
<th>Train</th>
<th>Carpooling</th>
<th>Free-use car</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (euros)</td>
<td>15</td>
<td>10</td>
<td>25</td>
</tr>
<tr>
<td>Time (mins)</td>
<td>75</td>
<td>65</td>
<td>55</td>
</tr>
<tr>
<td>Comfort</td>
<td>2</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

According to the definition in section IV and the data in Table 2 and the weight vector of the fitness function, we have $w_P = (0.5, 0.3, 0.2)$. The fitness function becomes:

$$f(x) = 5/x_1 + 19.5/x_2 + 0.2/x_3$$  \hspace{1cm} (6)$$

The number of requests varies significantly. The response time of the algorithm changes along with the quantity of requests. Figure 6 is the relation between the response time and request quantity. The response time is approximately linear with the request quantity. The proposed encoding method and EAs can cope with this type of problem without too long response time even big quantity of requests.
The following scenarios will show the respect of the travelers' preference and the rate of their satisfaction. The application of the EAs gives the following results:

(1) In case of sufficient resource of carpooling and free-use car (we consider the places in train are unlimited), the EAs will satisfy the travelers' choice and optimize the fitness function defined above. The fitness function is maximized with respect to the condition of availability of the relevant vehicles. The preference is given as Table 3, and we get Table 4 as the assignment matrix. The evolution of the fitness function is as the Figure 7. The rate of satisfaction of all the travelers is 100%.

(2) In case of insufficient resource of carpooling or car sharing, the applied algorithm will firstly meet the travelers' demands that are restrictive to only one method of transportation. Then the fitness function is maximized with respect to the condition of availability of the relevant vehicles. There are 30 service requests; meanwhile 5 carpooling places and 5 free-use cars are available. The users' preference is given as Table 5. Thus, we get Table 6 as the assignment result. The evolution of the fitness function is as the Figure 8. With the condition of the availability of the vehicles, the specific demand is met. Two requests with their first choices for carpooling and another two requests for free-use cars are allocated with train, all the rest satisfied for their first preferences.

(3) In case of insufficient resource of both carpooling and car sharing, the local search algorithm will applied. In the limit of the availability of the vehicles, the preference of the requests will be met as much as possible. There are 30 service requests and 5 carpooling places and 5 free-use cars available. The preference is given as Table 7, and we get Table 8 as the assignment matrix respectively. With the condition of the availability of the vehicles, the specific demand is met. Two requests with their first choices for carpooling and another two requests for free-use cars are allocated with train, all the rest are satisfied for their first preferences.

As the local search algorithm only charges the factors of preference and availability, no complicated combinatory will occur. This is reliable and feasible for little quantity of requests and insufficient vehicle resource.

**Figure VII:** The Evolution of the Fitness Function

**Figure VIII:** The Evolution of the Fitness Function
VI. Conclusions and Future Works

In this paper, an algorithm for the assignment of vehicles in a distributed co-modal transport information system is presented. The preference and the availability are both considered while the optimization. With the evolutionary algorithm and the local search algorithm, the system switches between them in favor of the response time. The part of simulation shows how the system works.

In the future work, the coalition of the segments will be studied. The combination of different routes represented by the Route Agent will be studied. This coalition is dedicated to the formalization of an optimized itinerary solution for the travelers. Especially, a protocol for the communication between the agents, which represent the segments, will be established. After the coalition procedure, a complete journey will be returned with the employed transportation.
service.

REFERENCES


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