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# The Crew-Scheduling Module in the GIST System

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Abstract

The public transportation is gaining importance every year basically due the population growth, environmental policies and, route and street congestion. Too able an e¢cient management of all the resources related to public transportation, several techniques from di¤erent areas are being applied and several projects in Transportation Planning Systems, in di¤erent countries, are being developed. In this work, we present the GIST Planning Transportation Systems, a Portuguese project involving two universities and six public transportation companies. We describe in detail one of the most relevant modules of this project, the crew-scheduling module. The crew-scheduling module is based on the application of metaheuristics, in particular GRASP, tabu search and genetic algorithm to solve the bus-driver-scheduling problem. The metaheuristics have been successfully incorporated in the GIST Planning Transportation Systems and are actually used by several companies.

# 1 Introduction

Public transportation companies are faced with important challenges in the area of transportation planning due mainly the growing importance of this mode of transport, especially in Europe. Some factors are forcing changes in the planning and management of the public transportation companies, private or public owned, creating the need of computerized transportation planning systems to aid these companies at several planning levels, strategic, tactical and operational. The main factors a¤ecting the public transportation are the population growth, environmental policies, the street congestion, parking policy and the growing limitations on private car utilization, especially in big cities. These factors have made a relevant impact on urban public transportation. The population will decide for public transportation if the quality of the service is adequate and, for other side, the public transportation companies need to manage e¢ciently their resources and, at the same time, o¤er a good service to their customers. Given a certain level of service, a large amount of money can be saved if the available resources are employed e¢ciently, or wasted if not. For inter-cities public transportation, the issues posed are very similar. Again, the concerns about environment, the routes congestion and the competition between several companies and other transportation modes are posing enormous challenges to the public transportation that operate between di¤erent cities or regions.

The success of the public transportation companies, given the present concerns, requires emphasis on e¢ciently planning all their activities with two main objectives: minimize the operational and total costs and o¤er a good service. To be able to respond to these challenges there is the need of sophisticated decision support systems based on powerful mathematical models and solution techniques, together with the advances in information and communication technologies. There is no doubt of the importance of quantitative models and computer based tools for decision making in today's business environment. This is also true for public transportation area. These computer-based planning transportation systems can make a signi…cant impact in the decision and operational process on these companies. That is why the academia and companies have become increasingly interested in transportation planning systems to be able to respond to the problems and issues posed in the area.

Several projects have been developed, or are undergoing development, to design a Transportation Planning System. Some of these projects are the HASTUS, Rousseau et al. (1985), IMPACTS, Smith and Wren (1988), HOT, Daduna and Mojsilovic (1988) and TRACS II, Kwan, Kwan, Parker and Wren (1997). All of these systems are used by transportation companies in several di¤erent countries, mainly for bus transportation and in some cases they have been extended to train transportation. For a survey in transportation planning see Odoni et al.(1994), Daduna et al.(1995), Wren and Rousseau (1995), Wren (1996) and for a survey in vehicle and crew scheduling see Freling (1997).

The present work is also a part of a large project in transportation planning, designated by GIST ("Gestão Integrada de Sistemas de Transporte" which translates in Integrated Management Transportation System), developed in IN-

EGI, University of Oporto and ICAT, University of Lisbon, in coordination with six Portuguese bus transportation companies: Carris, STCP, Horarios do Funchal, Vimeca, Barraqueiro and Rodoviária de Lisboa. GIST is a Decision Support System that assist the planning department of public and private transportation companies or transit authorities in their transportation operations management. The system includes several modules and interfaces to aid the planner in activities as the production of timetables, the scheduling of vehicles, the generation of daily duties for drivers, and the construction of duty rosters of individual drivers for a certain period. Many of these activities were usually planned by hand or using simple rules of thumb before the GIST system was installed. Therefore, the capabilities of the GIST system have made a strong impact on these companies by able them to analyze and plan their activities more e¢ciently within a shorter period of time.

The main objectives of this work is to present the Crew-Scheduling Module which is one of the most important and complex parts of the GIST system. In the next section, we describe the GIST system, and its basic components. In section 3, we describe the main issues within the Crew-Scheduling Module, and after, we discuss the important role that metaheuristics play to solve the problems of the Crew-Scheduling Module. In section 5 we brie‡y present some computational results for several instance of di¤erent companies of the GIST project, followed by some conclusions.

## 2 The GIST System

The GIST system is an integrated transportation planning system that assists the planning department of public transportation companies or transit authorities in their activities, as the optimization and planning of the public transportation. The actual system is an evolution of two other separate systems that were in use in three of the largest public transportation companies in Portugal: CARRIS, STCP and RODOVIARIA. In 1989, the GIST Consortium was establish under a Research and Development Agreement involving …ve public transportation companies, CARRIS, STCP, Horarios do Funchal, VIMECA and Barraqueiro and, two Operations Research units in two di¤erent universities, Faculty of Science in University of Lisbon and, Faculty of Engineering of the University of Porto. Later, other company jointed the project. The objective of the GIST Consortium was to develop and implement a new integrated decision-support system for the operation planning of all activities related with the public transportation of these companies.

GIST is highly modular decision support system, using state-of-the-art algorithms within user-friendly graphical interfaces. It is made up of a set of seven modules, each of them with a very clear de…ned function, assisting the user in each of the usual phases of the planning process. Each module is further organized o¤ering a set of interactions on working documents. The GIST system can be easily adapted or extended to suit particular needs of the actual users or new users. The GIST philosophy is to assist the user in producing the most desired solution. This means that any planning decision can either

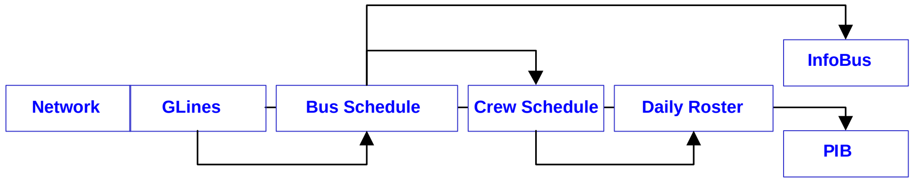


Figure 1: GIST Transportation planning modules

be produced automatically using state-of-the-art optimization algorithms and intelligent heuristics, or interactively changed, as the user …nds best.

Next, we will brie‡y review the GIST system. For a more complete description see the OR/MS Today article, Falcão e Cunha and Pinho de Sousa (2000).

In GIST system, the transportation planning is decompose in several modules due to its complexity: Network, GistLines, Timetabling and Vehicle Schedule, Service or Crew Schedule and Daily Roster. There are more two modules: InfoBus and PIB (Performance Indicators Board) that summarize the information of all other modules, see Figure 1.

² Network Modeling Module: maintains the information on the company operational network respecting to the nodes (terminus, relief points, etc.), segments, distances, types of days, periods of the day or year, etc. See Figure 2.

² GISTLine Module: maintains information on the company sets of routes, statistics and geographical information of the routes. The GistLines are resource management units, that allow a better planning dividing the network into smaller parts according to geographical areas and modes of transport (di¤erent types of buses or boat). The transport service is composed by a set of lines, identi…ed by a number, that correspond to a bus traveling between two points in town or between two towns. The use of the GistLines proved to be appropriate within the public transportation companies in the GIST project. See Figure 3.

² Timetable and Vehicle Module: de…nition and maintenance of all information about the trips, e.g. trip timetables for the GistLines, or set of routes along the days of planning. A trip is a movement of a vehicle in a given path. Therefore, it is the smallest job that can be assigned to a vehicle. For each line the respective frequency is determined based on demand and an appropriate timetable is generated for each season of the year, for each weekday and for each period of the day, resulting in trips that correspond to a start and to an end point, and a start and end time.

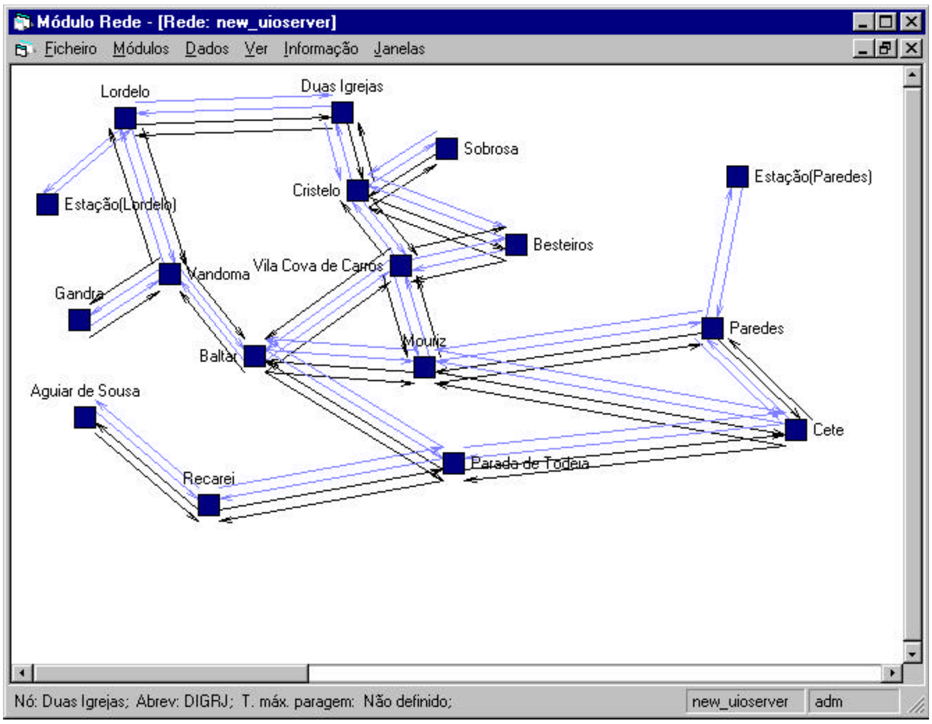


Figure 2: An operational network graphic

This module includes also the management of vehicle scheduling. This process automatically produces an optimized vehicle scheduling and able the user to evaluate and, manually or automatically, manipulate the system proposed solution. The services of the vehicles are set of trips, such that the timetabling is ful…lled and the schedule can be implemented. See an example of the interface of this module in Figure 4.

- Crew-Scheduling Module: management of the crew (bus drivers) scheduling by automatically producing a optimized bus-driver scheduling, and able the user to evaluate and, manually or automatically, manipulate the system proposed solution. In next section we will describe in more detail this module, since is the main object of this work.

- Crew-Roster Module: this module constructs monthly rosters comprising the daily duties of individual drivers together with their days o¤ and holidays.

Any of the modules are capable of producing documents and reports with the related information, and also graphical and tabular visions of the data, indicators, evaluation functions and solutions related with each module. This interface capability of the GIST system is a very important aspect since able the users to interact with the system. See an example of the graphics and tables capabilities in Figure 5.

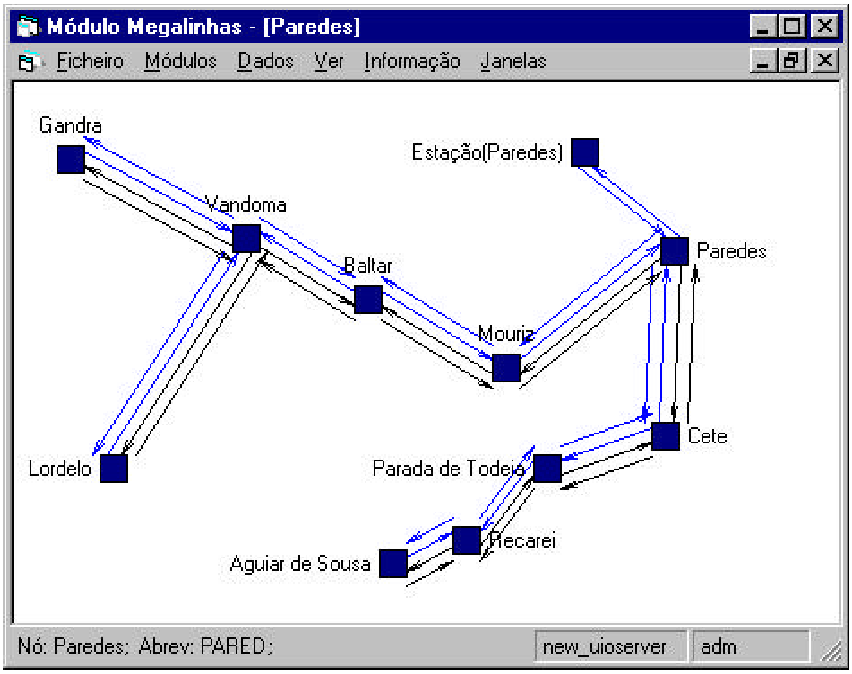


Figure 3: A GISTLine

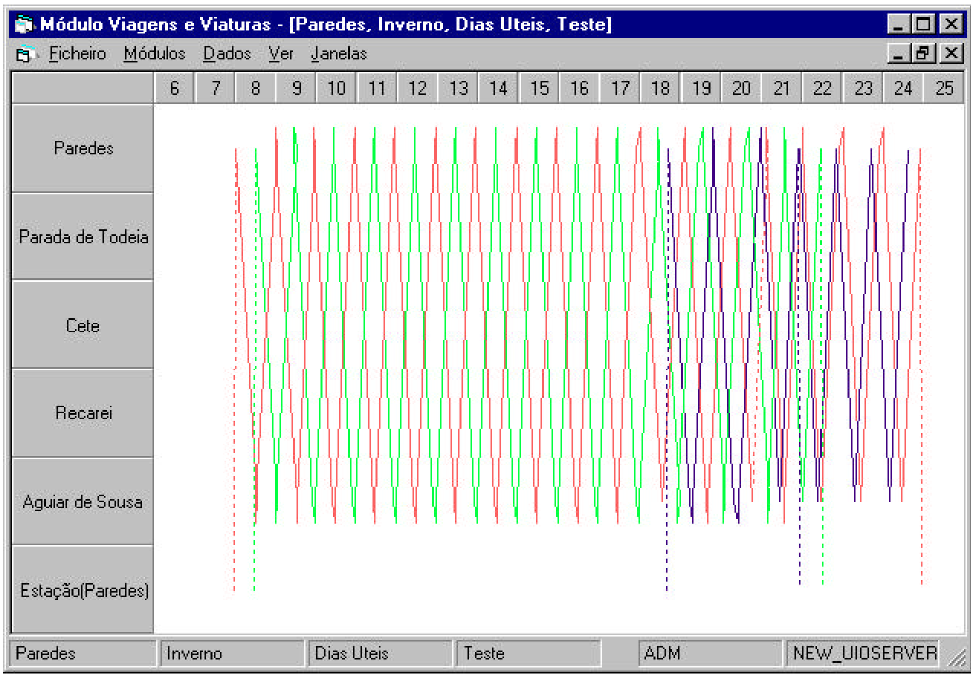


Figure 4: An example of a timetable and vehicle module interface

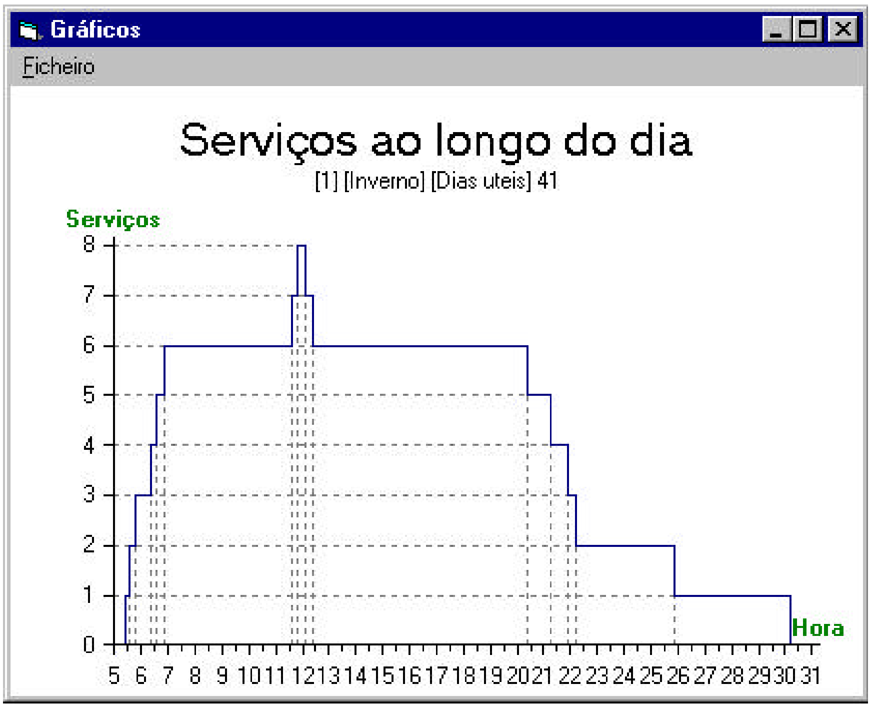


Figure 5: Duty needs during a day

The GIST system has two basic modules that rely heavily in optimization models and methods, the Vehicle and Crew-Scheduling Modules. The Vehicle-Scheduling module is based on the work of Mesquita and Paixão (1996) and Paixão and Branco (1996) and is well suitable for the expectations of the users. However, the original Crew-Scheduling module based on Integer Linear Programming techniques was not well accepted by the users since, in they opinion, the automatic solutions could not be implemented in practice without an enormous e¤ort of adaptation. In the next section we will discuss more in detail this problematic in the Crew-Scheduling module, and afterwards we describe the solution implemented actually working in the GIST System.

# 3 The Crew-Scheduling Module

The Crew-Scheduling Module includes automatic interactions to produce daily duties for the drivers. It allows the user to visualize and manipulate the solutions and to evaluate their quality, according to econometric parameters, de…ned duty types and scheduling rules. The main issue of this module is the automatic generation of the daily feasible and best duties to cover all the trips for a speci…c day and timetable. This is a well-known problem in Operations Research literature: the crew-scheduling problem.

Traditionally, the crew-scheduling problem has been formulated as a single objective integer linear program and several Linear Programming methods have been proposed to solve it. These methods have been widely applied by the previously mentioned systems. The GIST system used, until recently, an algorithm based on Linear Programming, Beasley (1987) and the Vasko and Wolf (1988) heuristics to obtain lower and upper bounds for the problem, formulated as a Set Covering model. However, the bus companies involved in the GIST project were not satis…ed with the bus-driver module based on single-objective LP, even the optimal cost solution could be obtained for most instances. The users complain that the automatic solution could not be implement in reality and were not adequate to their expectations and problematic. The transportation companies may have several di¤erent objectives when planning besides the cost function, as for example the service quality, which can be measured in di¤erent ways in each company. We asked the companies to give us a good solution for them, …nding the cost to be high when we plugged in it into the single objective model. To be able to produce a more realistic model of the problem we have to consider several objective functions linked to the service quality that usually are in con‡ict with the traditional cost function.

In the GIST system development, we put emphasis in taking into account the environment of the users of the GIST system when developing the solution methods. In everyday planning, these companies need fast methods to obtain several good scenarios that can help the decision-maker. Therefore, the aim was to develop methods to solve real-world crew scheduling problems that can be used in a transportation planning system for these companies, in a user-friendly environment. The methodology followed to develop such a solution approach was the multiobjective metaheuristics since they can obtain e¢cient solutions in a short time considering the multiobjetive approach, allowing, after the decision maker to do what he or she does best, making judgments in the face of the set of several good scenarios. The ultimate objective is improvement of real managerial and operations e¤ectiveness. Next we will describe the model adopted and afterwards we will describe the metaheuristics applied in the GIST System.

The bus-driver scheduling problem (BDSP) stated as …nding a set of feasible daily duties that cover all trips or vehicle blocks. A vehicle block is the itinerary of a vehicle between its departure from the depot and its return to the same depot. Any vehicle block can be split into pieces of work, such that a split occurs only at a relief opportunity, i.e. a time and a place at which change of drivers is possible. A driver's duty is a set of pieces of work that can be assigned to a driver.

Several formulations have been proposed for the single objective crew-scheduling problem. We will consider an approach based on the set covering formulation of the problem, considering multiple objective functions. One of the advantages of the set-covering formulation is that it is independent of labor contract and speci…c company rules. Therefore, the duty generation module is separated from the duty selection module where the minimal cost or best quality driver duties are chosen such that all pieces of work have a driver. The set of the driver duties is generated by an algorithm presented in Agra (1993). The method iteratively generates combinations of pieces of work that complies with labor contracts and company rules, speci…c for each company, as for example no duties with more than four hours lunch break. This procedure is tailored to each company since each company has its own rules mostly based on union agreements and operational rules. The separation between duty generation process and duties selection allows us to adjust only the first module for each transportation company and therefore, is very convenient for implementation reasons.

Let $M = \{1, 2, \ldots, m\}$ and $N = \{1, 2, \ldots, n\}$ be the index sets for the pieces of work (rows) and feasible duties (columns), respectively. Define the matrix as follows:

$$a_{ij} = \begin{cases} 1 & \text{if the duty index } j \text{ includes the } i\text{-th piece;} \\ 0 & \text{otherwise.} \end{cases}$$

Consider the following variables:

$$x_j = \begin{cases} 1 & \text{if } j\text{-th duty is in the solution;} \\ 0 & \text{otherwise.} \end{cases}$$

For each duty, a cost is associated which represents real cost as extra hours, night hours and meal costs, and artificial costs, such as, vehicle change, duty type, and number of hours over the average. Other components of the cost can be considered the transportation company requests them. Let $c_j$ be the cost associated with duty $j$ and define the cost function as $f_1(x) = \sum_{j=1}^{n} c_j x_j$.

In the previous formulations the objective was to minimize the total cost of the driver's duties. However, the single objective approach had been object of criticism by the bus companies in the GIST project since during planning they also want to take into account other objectives like service quality. Different companies may have different measures of the service quality, but all of them agree in the importance of taking other objectives besides cost when planning. Moreover, they want to be able to analyze several scenarios before taking a decision. Therefore, a multiobjective combinatorial optimization model is appropriate to formulate the BDSP. Some examples of measures of the quality of the service are:

- The number of pieces of work not covered. Some companies allow pieces of work or trips to be uncovered. However, a good schedule should have a small number of these pieces. The objective function is:

$$f_2(x) = \sum_{i=1}^{m} \max\left\{1 - \sum_{j=1}^{n} a_{ij} x_j ; 0\right\}.$$

- The unfitness value, which measures the amount of infeasibility with respect to the set partitioning formulation, Chu and Beasley (1995). We define the unfitness by $\sum_{i=1}^{m} |w_i - 1|$, where $w_i = \sum_{j=1}^{n} a_{ij} x_j$ as the number of columns in the current solution $x$ that cover row $i$. In practice this value is quite important for the users. Some degree of overcovering is desired. However, if a solution has some pieces of work with too many drivers assigned, the planner will have to adjust manually this solution until he or she obtains one with smaller unfitness value. Therefore, we have defined the unfitness function as:

$$f_3(x) = \sum_{i=1} \left| \sum_{j=1} a_{ij} x_j - 1 \right| .$$

- The total number of duties. Some companies claim that a small number of duties respecting the labor and company constraints allow a better planning and easier implementation. Define the "number of duties" function as:

$$f_4(x) = \sum_{j=1} x_j .$$

- The total number of duties with only one piece-of-work (trippers). Trippers are duties that cover only one piece of work, which usually are very expensive to implement. Therefore, some companies use them only in special cases and want to minimize the use of these type of duties. The objective function is:

$$f_5(x) = \sum_{j:\sum_{i=1}^{m} a_{ij} = 1} x_j .$$

- The number of vehicle changes. The change of a vehicle driver can disrupt the operations of the company and cause complaints from the drivers. Therefore, some companies are mostly worried about minimizing the number of changes. Supposing the columns are ordered such that the last $q$ are the duties with vehicle changes, the objective function is

$$f_4(x) = \sum_{j=1=n-q+1} x_j .$$

Other objective functions can be considered as well as some combination of any of the above functions.

The BDSP can be formulated as a multiobjective set-covering problem, where is the number of objective functions to be considered:

$$\text{Min} \quad z(x) = (f_1(x), f_2(x), \ldots, f_K(x)) \qquad (1)$$

$$\begin{aligned} \text{s.t.} \quad & \textstyle\sum_{j=1}^{n} a_{ij} x_j \geq 1, \quad i \in M; \qquad (2) \\ & x_j \in \{0, 1\}, \qquad j \in N. \qquad (3) \end{aligned}$$

Columns correspond to duties and the rows correspond to the pieces of work. We say that row $i$ is covered if there exists a column $j$ in the solution such that

$a_{ij} = 1$. Constraint (2) means that every piece of work has to be covered by at least one duty. This means that there exists a driver's duty $j$ in the solution that contains the piece of work $i$.

The single-objective set-covering problem (SCP) is NP-hard, Karp (1972), Garey and Johnson (1979). Several approaches have been proposed to solve the SCP, based on heuristics, column generation, lagrangian and linear programming relaxations and state space relaxation, see for example Caprara, Fischetti and Toth (1999) as one of the last proposed heuristics for the SCP. Other surveys can be found in Odoni et al.(1994), Freling (1997) and Daduna et al.(1995). Several greedy heuristics, based on di¤erent priority or greedy functions presented in Vasko and Wolf (1988). Beasley and Chu (1996), Al-Sultan et al.(1996), Clement and Wren (1993). Wren and Wren (1995), Kwan and Wren (1996), Kwan, Kwan and Wren (1997), Portugal (1998), and Galvão, Sousa and Cunha (1998) have proposed some approaches based on genetic algorithms (GA).

Multiobjective optimization has been vastly studied, see Steuer (1986) for a basic reference. One property that is commonly considered as necessary for any candidate solution to the multiobjective optimization problem is that the solution is not dominated.

A feasible solution $x$ is dominated by a second feasible solution $y$ if and only if $f_k(y)$ $f_k(x)$ for $k = 1; :::; K$, and $f_k(y) < f_k(x)$ for at least one $k$. A feasible solution is e¢cient if, and only if, there is no other feasible solution, which dominates it.

In classical literature on muldimensional optimization problem, the usual approaches are to aggregate all the objectives in a utility function and solve the problem as a single objective problem or use interactive method, see Steuer (1986). However, knowing the set of e¢cient (Pareto-optimal) solutions, or an approximation of it, gives greater freedom to the decision-maker when selecting solutions. However, …nding this set is a complex task. If several e¢cient solutions are known by the user, this one can compare them even with respect to additional criteria which have not been formalized, e.g. the acceptance by management or the public. Note that this is exactly the objective that the transportation companies involved in the GIST project are looking for. Moreover, since we are working with di¤erent companies, the criteria to choose one solution over another can be di¤erent amongst the various companies. The possibility of analyzing several scenarios of e¢cient solutions is a very important aspect for the companies in order to accept the transportation planning system. For all these reasons, some of the classical methods are not adequate. The recent advances and success in multiobjective metaheuristics applied to other problems advocate the use of these techniques as a good way to proceed.

## 4 Metaheuristics for the Crew-Scheduling module

Metaheuristics have many desirable features to be an excellent method to solve very complex problems: in general they are simple, easy to implement, robust and have been proven highly e¤ective to solve hard problems. Even in their most simpler and basic implementation, the metaheuristics have been able to effectively solve very hard and complex problems. The metaheuristics modular nature leads to short development times and updates, given a clear advantage over other techniques for industrial applications. Another aspect that we would like to mention in favor of using metaheuristics is the estimation of costs, that instead of obtain one optimal solution, the user prefers to produce several scenarios for the same problem. For example, various possible scenarios representing a variety of possible future demand patterns or transportation costs can be generated. These scenarios can then be directly incorporated into the model. The scenario-based approaches can incorporate a metaheuristic to obtain the best possible decision within a scenario. The combination of best characteristics of human decision-making and computarized model and algorithmic based systems into interactive and graphical design frameworks have proven to be very effective in GIST system. Recently there has been an increasing interest in applying metaheuristics to multiobjective problems, see Viana and Sousa (1999), Hansen (1997) and Fonseca and Fleming (1995).

To solve the BDSP we have implemented three metaheuristics: GRASP, Tabu Search and Genetic Algorithms. Next, we will present the most relevant aspect of these metaheuristics. For a more complete description see Lourenço et al. (1998).

The Greedy Randomized Adaptive Search Procedure, GRASP, was proposed by Feo and Resende (1989), and since then it has been applied to several Combinatorial Optimization problems with success. The GRASP repeats a construction phase based on a greedy heuristic follow by a local search method. In our application, the following greedy function is applied: $\frac{c_j}{k_j}$ where $c_j$ is the cost of column $j$ and $k_j$ is the number of uncovered rows that column $j$ covers if added to the solution. The second phase of the GRASP is a first-improvement local search heuristic based on the exchange neighborhood. The exchange neighborhood consists on removing a column of the solution and adding a new column that covers at least one of the uncovered rows.

The next metaheuristic proposed to solve the BDSP is based on Tabu Search, Glover (1986), Glover and Laguna (1997). We have implemented a Multiobjective Tabu Search which considers a set of weights assigned to each objective function and a utility function that is the weighted sum function, Hansen (1997) and Viana and Sousa (1999). In our implementation, we apply initially a tabu search considering one objective function at each time and try to obtain the best solution with respect to this objective function. Afterwards, we apply the tabu search using the weighted sum function to obtain additional efficient solutions. In the diversification steps, the weights are modified in such a way that the search tries to look for new nondominated solutions by using the information obtained in previous runs and the values of the objective functions for each individual run at first step. All nondominated solutions found are stored and output at the end of the search. The initial solution can be obtained by two methods: a random initial heuristic and a greedy heuristic. We considered three neighborhoods, the exchange neighborhood, the remove neighborhood and the insert neighborhood. Two tabu lists were considered: the insert tabu list and the remove tabu list. An innovated aspect considered in the tabu search is the optimized intensification strategy which consists in applying the tabu search for several iterations using only the insert neighborhood. The resulting solution has a large number of columns and each row is covered by several columns. To obtain good solutions with fewer columns and, such that, each row is not overcovered, we can apply an exact method or GRASP method to the set covering subproblem using any objective function.

The last metaheuristics developed is a Genetic Algorithms (GA), Holland (1975) and Davis (1991). The population-based search of the GA makes this approach tailored to solve multiobjective optimization methods. See Fonseca and Fleming (1995) for a discussion in the use of genetic algorithms to multiobjective problems. The GA proposed to solve the BDSP is based on the work of Beasley and Chu (1996), but considering the multiobjective aspects of the problem. Solutions are represented as a binary vector of dimension n, indicating if the column (driver duty) is or is not in the solution. The initial population is generated by different methods to guarantee some diversification. The first method generates random solutions as follows: for each row, choose randomly a column that covers it, and then apply a simple heuristic to eliminate columns that cover already covered rows. The remaining solutions are obtained by the heuristics described in Vasko and Wolf (1985) so we guarantee the presence of some good solutions in the initial population in order to make the search converge faster. The initial population has 100 solutions and, as the offsprings are introduced into the population, it can grow until 200. When this limit is obtained, we choose the 100 best solutions and eliminate the remaining ones. The parents are selected by a tournament selection based on the uniform probability function and on the different objective functions. In the multiobjective approach different objective functions are used to determine the best solution of each group. We use a two-point crossover and the mutation operator proposed by Beasley and Chu (1996) based on removing or including a column. After the crossover and the mutation, an offspring solution can be included in the population or not, depending on the dominance criteria. The final population will be an approximation of the set of efficient solutions since the nondominated solutions within a population are maintained from generation to generation. At the end, the system presents these "near" nondominated solutions to the users to be considered in the planning process. The generation of a population of solutions allow the user to evaluate several scenarios after one run of the solution method and dynamically interact with the system.

An improvement in the GA was obtained by defining a new crossover operator that we denominate by perfect offspring. This operator considers two parents and tries to obtain the best offspring of these parents by solving a set-covering sub-problem, where only the columns present in the parent solutions are taken into account. We follow the optimized intensification strategy described previously, which consists in applying exact methods for small instances and the GRASP method for larger ones. The perfect offspring crossover allows the search to converge rapidly to efficient solutions and this idea can be applied to other combinatorial optimization problems.

The metaheuristic method have been successfully incorporated in the Decision Support System for Transportation Planning GIST, allowing solving very

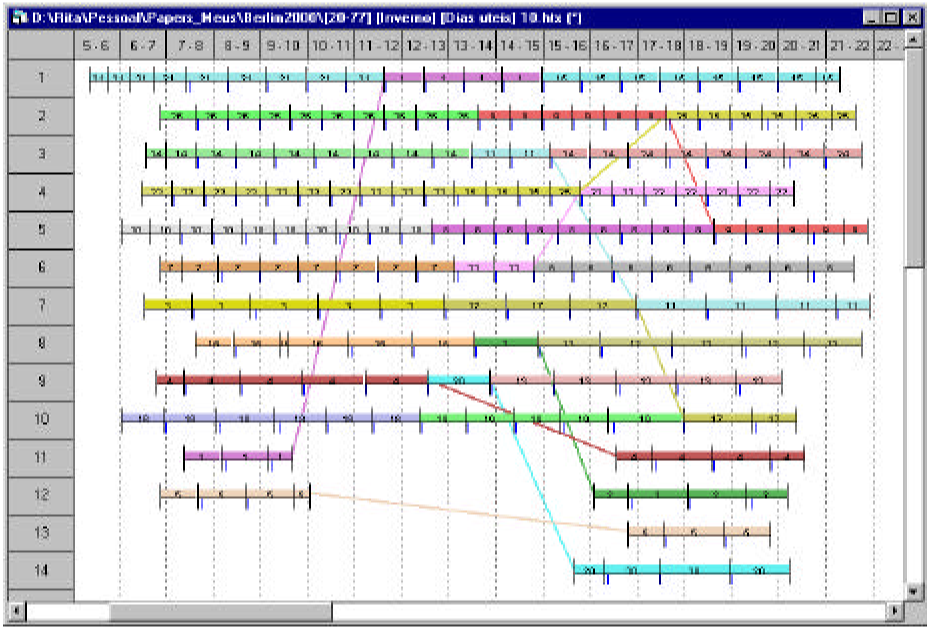


Figure 6: Mnual obtained solution

large-scale problems during the planning process, substituting the previous LP-based method that was criticized by the users. The LP method was able to find the optimal solutions with respect to the cost function for the large majority of the instances. However, the solutions usually had some characteristics that were difficult to implement, or were not accepted by the management. The use of the multiobjective metaheuristics lead to better acceptance by the users of the crew-scheduling module of the GIST system, creating real schedules that meet the requirements of the final users. Moreover, the GIST system, using these new methods to build bus driver schedules, permited the achievement of a final solution that needs much less manual adjustment by the user than before, a common practice for the LP-based solutions. An additional advantage of the multiobjective metaheuristics is the possibility to incorporate, in an easy way, the use of different objective functions. The minimization of the changes necessary for adjusting the objective functions is very important aspect in the design of the GIST system.

In Figure 6 and 7, we present two solutions of the Crew-Scheduling module to the same problem, the first generated manually by the user after a long period of work and the second generated by the GA after some seconds. Both solutions have 26 services and all the other objective functions are similar, except that the first one is more expensive than the second one, 112088 versus 108094. Notice that the solution are quite similar, which represent exactly what the users were looking for. The previous method used in the GIST system was able to find lower cost solutions, but they were substantially different from the ones that the user were looking forward, for example, with a large amount of duties with 3 or more vehicle changes. The metaheuristics can find low cost solutions with

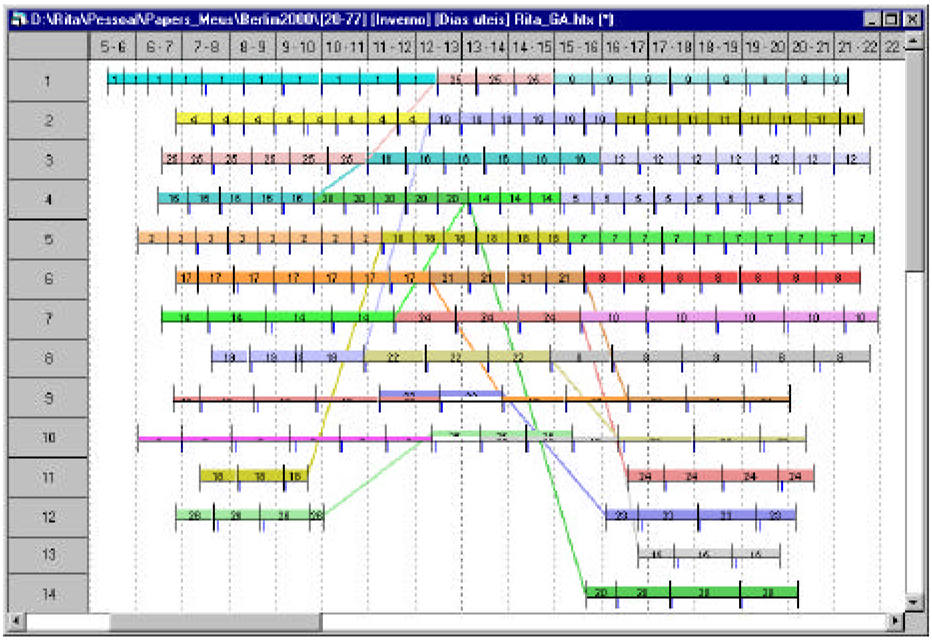

Figure 7: Automatic solution obtained by the GA

the expected characteristics that users are looking for.

# 5 Computational Results

We have done several tests on real instances from companies that actually use the system in their daily work. In Portugal (1998) there is a complete description of those tests, and their complete analysis. In this work, we selected three companies trying to show the big diversity of rules and labor legislation that de…ne the bus driver duties properties. These examples represent the usual dimension of the problems that the users deal in practice in some of the companies. The tests were made in a Workstation IBM Risc 6000.

After describing the data properties, we present the solutions comparing the previous GIST algorithm with the new metaheuristic based algorithms.

The main properties of instances from Rodoviária de Lisboa (RL) are:

² Bus timetable with 38 vehicles, 29 involving all day (from 6 a.m. to 11 p.m.) and the others only involving some part's of the day split in one or two periods (6 a.m. to 10 a.m. and 5 p.m. to 8 p.m.);

² One depot;

² Five relief points;

² Duty types with 2 or 3 stretches;

² Maximum extra hours: 4 hours;

- No …x meal period;
- One maximum vehicle change;
- Normal work duration of 8 hours or 12 hours in duties with extra time;
- Break time between 1 and 3 hours. In 3 stretches duties the second break correspond to a technical rest and is duration is 30 minutes to1 hour;
- Short breaks maximum duration of 1 hour.

The main properties of instances from Horários do Funchal (F) are:

- Bus timetable with 14 vehicles, 6 involving all day (from 6 a.m. to 12 p.m.) and the others only involving some part of the day split in two or three periods (7 a.m. to 10 a.m., 12 a.m. to 2 p.m. and 6 p.m. to 9 p.m.);
- One depot;
- One relief point;
- Duty types with 1 or 2 stretches;
- No extra hours;
- No …x meal period;
- Two maximum vehicle change;
- Normal work duration of 8 hours;
- Break time between 1 and 3 hours;
- Short breaks maximum duration of 45 minutes.

The main properties of instances from STCP (S) are:

- Bus timetable with 21 vehicles, 15 involving all day (from 5 a.m. to 21 p.m.) and the others only involving some part of the day split in two or three periods (6 a.m. to 10 a.m., 12 a.m. to 3 p.m. and 4 p.m. to 9 p.m.);
- One depot;
- Two relief points;
- Duty types with 1 or 2 stretches;
- No extra hours;
- One hour meal period from 10 a.m. to 3 p.m.;
- One maximum vehicle change;
- Normal work duration of 6 hours and 30 minutes;

- Break time between 1 and 2 hours. There is one duty type with break time between 2 and 7 hours:
- No short breaks;

Dimension of the examples used in computational tests, the nlig is the number of one in the matrix A:

| | m | n | nlig |
|---|---|---|---|
| RL | 215 | 8511 | 37450 |
| F | 141 | 39842 | 258169 |
| S | 303 | 76783 | 552703 |

The results are presented in the following table:

| | | Cost | Un…t | Duties | Trippers | Over-cover rows | Not cover rows | Time |
|---|---|---|---|---|---|---|---|---|
| Previous method | RL | 467254 | ¡ | 63 | 6 | 34 | 0 | 5m26s |
| | F | 167321 | ¡ | 28 | 0 | 39 | 0 | 19m9s |
| | S | 229477 | ¡ | 51 | 1 | ¡ | 0 | 48m20s |
| GRASP | RL | 482876 | 51 | 66 | 6 | 46 | 0 | 15m8s |
| | F | 165244 | 60 | 28 | 1 | 36 | 0 | 43m33s |
| | S | 235554 | 121 | 51 | 0 | 71 | 0 | 54m54s |
| PTS | RL | 466797 | 39 | 53 | 0 | 25 | 13 | 9m32s |
| | F | 166028 | 41 | 22 | 0 | 25 | 7 | 5m51s |
| | S | 269668 | 176 | 58 | 0 | 93 | 0 | 1m |
| PTDI | RL | 532498 | 79 | 73 | 2 | 44 | 7 | 4m4s |
| | F | 162708 | 33 | 21 | 0 | 20 | 7 | 6m11s |
| | S | 300106 | 180 | 59 | 0 | 79 | 0 | 33m54s |
| GA | RL | 463840 | 38 | 61 | 6 | 35 | 0 | 5m23s |
| | F | 177426 | 78 | 29 | 0 | 55 | 0 | 59m54s |
| | S | 308003 | 133 | 54 | 0 | 91 | 0 | 55m6s |

The value "Time" correspond to necessary time to obtain the solution describe on the table.

In RL example, GA's improve "Cost" and "N. Duties" values. The PTS algorithm improves the number of over cover rows but the solutions have more rows not cover. The value of "N. Tripper's" is quit the same in all algorithms.

In F example, GRASP improve the "Cost" and "N. Overcover Rows" values. Both Tabu Search Algorithms improve "Cost", "N. Duties" and "N. overcover Rows" but the number of not cover rows increase.

In S example, for "Cost" and "N. Duties" the previous method gave the better values. Between the new algorithms, GRASP gives better values to "Cost" and "N. Overcover Rows". The "N. Tripper's" is quite the same in all metaheuristic algorithms and is better than the previous methods value.

## 6 Conclusions

Several public transportation companies, representing more than half of the bus and coach transportation market in Portugal, are using the GIST System at different stages (complete system or some of their modules). The GIST system has been one of the most successful applications of OR in Portugal. The system can be viewed as a way to efficiently link optimization, which are good for determining quantifiable best solutions, with human decision-making process, which is good for understanding and integrating nonquantifiable issues.

The GIST project has been a unique opportunity for Operations Research, and in particular for metaheuristics, at transportation companies involved in the development of the GIST system. The use of metaheuristics is especially appropriate to integrate within a DSS that requires human intervention. The model is an integral part of the decision process, with the speed and accuracy needed to support the decision at hand. The GA and TS algorithms for the bus-driver scheduling, within the crew-scheduling module, play an important role in helping the decision-maker. These algorithms able the user to obtain several scenarios with only one run of the algorithm.

The modularity of the GA and TS make them specially suitable to solve complex problem, independently of the specific mathematical characteristics of the problems, as liner or non-linear functions. Moreover, since the methods share modules, it would be easy to implement several metaheuristics for the same problem on hand and to adjust each method to each company involved in the project. One of the main barrier that we have found previously the utilization of the metaheuristics in the crew-scheduling module was the difference in the objective functions of each company. By using the GA and the TS, this difficulty was overcomed since the methods require only a small change in the procedure to calculate the objectives values. Also, the inclusion of several objective functions in the set-covering model of the bus-driver scheduling made more realistic the model and better accepted by the users of the system. Our computational testing showed that the Multiobjective Tabu Search and the Multiobjective Genetic Algorithms lead to good results within reasonable times, as well as, results that compare favorably with the LP-based solutions. The users can now choose between any of the three methods and obtain several scenarios for a final decision in the planning process.

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