Multiobjective vehicle type and size scheduling problem in urban public transport using MOCell

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Abstract— **We study the problem of vehicle scheduling in urban public transport systems taking into account the vehicle-type and size (VTSP). It is modeled as a multiobjective combinatorial optimization problem. A heuristic based on MOCell (cellular evolutionary algorithm) is proposed to solve the problem. A set of non-dominated solutions represents different assignments of vehicles to specific routes. The conflicting objectives of provider and users (passenger) are to minimize the total operating cost, and maximize the quality of service, taking into account restrictions of government agencies in context of smart cities to improve the Intelligent Transport Systems (ITS).**

Keywords— **Evolutionary algorithms, multiobjective optimization, public transport, smart cities.**

I. Introduction

Cities around the world are in state of permanent flux and exhibit complex dynamics. A sustainable urban development is a complex problem and has received attention from researches for many decades.

In increasingly interconnected and globalized world, more than half the population (54%) are located in urban areas, unlike 30% in 1950. This abrupt growth implies deep changes in size and distribution of space (people per square meter). This effect will be accentuated in the coming years. An estimated increase in 2050 at 70% of the world population will live in cities [1]. It leads to rise demand for all infrastructures that interact directly with the people, who spread to urban areas hoping to find better job opportunities and a higher quality of life. However, the increase of migrants involves various problems such as congestion, increased demand for a limited supply of natural resources and other types of goods and services including energy, water, education, health and transportation.

The main challenges for cities on urban mobility are often related to the inability of public transport systems to supply needs of a growing number of users. Though each city has different extra issues, authorities and responsible agencies of the mobility share common challenges such as reduce congestion by improving traffic flow, sustainable and cleaner environment, increase the use of public transport, and other greener options such as bikes.

Harrison et al.[2] stated that the term “smart city” denotes an “instrumented, interconnected and intelligent city” [3]. Different areas such as public administration, education, health services, public safety, energy, transportation and logistics can be improved to make more intelligent, interconnected and efficient by computing technologies [4]. Smart cities can reduce costs, make responsible use of resources and encourage the active participation of citizens in decision-making processes, in order to achieve a sustainable and inclusive city.

The Intelligent Transportation Systems (ITS), also known as smart mobility, are a set of Information and Communications Technologies (ICT) applied for the specific case of transports. Technological advances in computer science and communication systems allow to collect a huge amount of transport and mobility data from citizens and get useful information to make new software tools e.g. interactive systems, algorithms and mobile applications, to benefit users, government organizations and service providers [5].

The main objectives of ITS are: improve the safety, increase efficiency and capacity, reduce energy consumption and negative environmental impact, enhance economic productivity for users and providers, enhance the personal mobility, convenience, and comfort and create an environment in which the development and deployment of new ITS technologies may appear.

This paper presents a heuristic based on multiobjective cellular evolutionary algorithm (MOCell) to solve the vehicle-type and size scheduling problem (VTSP), a variant of the vehicle scheduling problem. The objectives of ITS are conflicting goals due to the provider is seeking to minimize the operating and purchasing cost, and user want and expect a better service. Hence, a solution of our algorithm for VTSP proposes a distribution of vehicles (proper frequency calculation) to reduce the cost, and guarantee the quality of service.

II. Related work

This section presents a brief overview of different models and algorithms for transport problems, particularly urban public transport (Fig.1). Most of these works are based on models proposed decades ago applying computational intelligence techniques to improve approximate solutions, since the problem is NP-hard.

To plan a transport route, it is necessary to solve all the associated problems. To provide solutions, Ceder [6] and Wilson propose activities, usually performed in sequences as follows: network route design, setting frequencies, timetable development, vehicle scheduling and crew scheduling or driver scheduling

It is desirable, therefore, that all five activities be planned simultaneously in order to exploit the system capability to the greatest extent and maximize the system productivity and efficiency.

A. *Early heuristic methods*

So-called early methods were not very advanced, as nowadays, because computers have not enough power to run complex mathematical solvers and use techniques for mathematical models. Many approaches were reduced to construction of an initial schedule by using heuristic process, and, then, attempting to improve this schedule by making limited changes.

TRACS (Techniques for Running Automatic Crew Scheduling) was developed at the University of Leeds in 1967 [7]. The system is based on the assumption that a poor initial solution cannot turn into a good solution by heuristic improvements, which might be true since metaheuristics were not available at that time.

B. *Mathematical programming methods*

The vehicle or driver scheduling problem can be formulated as a set covering problem and expressed as an Integer Linear Programming (ILP) problem. The basic model is given below: number of potential changes (n), number of work pieces to be covered (m), cost of changes (c_j), $a_{ij} = \{0,1\}$, 1 indicates that the change j covers work piece i, and 0 otherwise. $x_j = \{0,1\}$, 1 indicates that the change j is used in the solution, and 0 otherwise. The objective is to Minimize $\sum_{j=1}^{n} c_j x_j$, subject to: $\sum_{j=1}^{n} a_{ij} x_j \geq 1$, $i \in \{1,2,...,m\}$, $x_j = 0$ or 1 , $j \in \{1,2,...,n\}$.

IMPACS (Integer Mathematical Programming for Automatic Crew Scheduling) was developed for bus operation in the late 1970s. Parker and Smith presented the prototype and Wren and Smith [8] gave a full description of the system. It was installed in London Transport in 1984 and in Greater Manchester Buses in 1985.

C. *Metaheuristic methods*

Methods for solving combinatorial problems can be classified into exact and heuristic. The exact methods guarantee to find the global optimum, but there are very few applications, due to its inefficiency by the high dimensionality of problems. Heuristics or metaheuristics allow approximate global optimum, however, they are more efficient and flexible.

Baaj and Mahmassani [9] propose a heuristic solution based on the combination of routes, where the initial population is generated from identifying the shortest paths between nodes of high demand. The model includes several restrictions with important issues in ITS.

d_{ij}	:	demand between nodes i and j
t_{ij}	:	total travel time between i and j
f_k	:	frequency of buses operating on mute k
f_{min}	:	minimum frequency of buses operating
t_k	:	around trip time of route k
Q_k^{max}	:	maximum flow occurring on any link of route
α	:	seating capacity of buses operating
LF_k	:	load factor of route k
LF_{max}	:	load factor of route maximum
N_k	:	number of buses operating on mute k
FS	:	fleet size
R	:	set of routes
C_1, C_2	:	weights reflecting importance of the two cost.

The objective is to minimize $\left[C_1 \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} t_{ij} + C_2 \sum_{j=1}^{n} f_k t_k\right]$, subject to: $f_k \geq f_{min} \; \forall \, k \in R$, $LF_k = \frac{Q_k^{max}}{f_k \alpha} \leq LF_{max} \; \forall \, k \in R$, $\sum_{k \in R} N_k = \sum_{k \in R} f_k t_k \leq FS$.

A local search algorithm proposed by Israeli and Ceder [6], for a multiobjective optimization to minimize the size of the fleet and cost that represents the number of passengers per hour, waiting time of passengers between each stop and travel time when the bus is empty.

$$\text{Min } f_1 = \left[C_1 \sum_{i,j \in N} PH_{ij} + C_2 \sum_{i,j \in N} WH_{ij} + C_3 \sum_{r \in R} EH_r\right]$$

$$\text{Min } f_2 = FS$$

Where EH_r is Empty Space Hours on route r, FS is Fleet Size and R is a set of routes, PH_{ij} is Passenger Hours and WH_{ij} is Waiting Time between nodes i and j.

The problem has been resolved in three stages: first, several sets of non-dominated solutions are generated by solving the problem associated covering sets and dispatch frequencies for each vehicle is determined. Local search method is implemented for exploring solutions, finally, they are evaluated and best solutions are selected from the Pareto-optimal set.

A number of GAs have been developed for the vehicle scheduling problem. Pattnaik et al. [10] focus on minimizing the cost associated for both the provider and users. Chakroborty [11], [12] highlights the high effectiveness of genetic algorithms to solve urban transit network design problem.

Shen and Kwan [13] develop HACS, with a Tabu search for the driver scheduling problem. The HACS approach is based on a representation of the problem involving sequences of links. The links and its associated active relief opportunities compose a solution space.

Costa et al. [14] present an algorithm in the field of high-speed trains. It is initialized randomly and uses classical techniques to improve cooling solution and escape from local optimal. The difference with classical simulated annealing algorithms of single objective is the use of weighted aggregation rules of values of objectives.

Recently, Mehr et al. [15] implement a metaheuristic based on ant colony systems for solving the problem of design lines of light rail and bus rapid transit in the city of Mashhad in Iran.

III. The multiobjective VTSP

Smart city's issues propose the development and implementation of computational techniques for planning mobility. ITS includes three main participants:

- Citizens or public transport users, looking for an efficient, economical, safe, comfortable and friendly multimodal system with the environment.
- Companies providing transport service, which mostly seek to reduce operating costs and maximize profits, focusing efforts on economic subjects under the regulations of government authorities.
- Governments whose policies seek to ensure a quality of life for its citizens, setting patterns of demand for mobility that meets their needs and ensuring the proper functioning of mobility systems.

We defined the problem taking as reference the bus transport systems, which can be extrapolated to other schemes without significant changes.

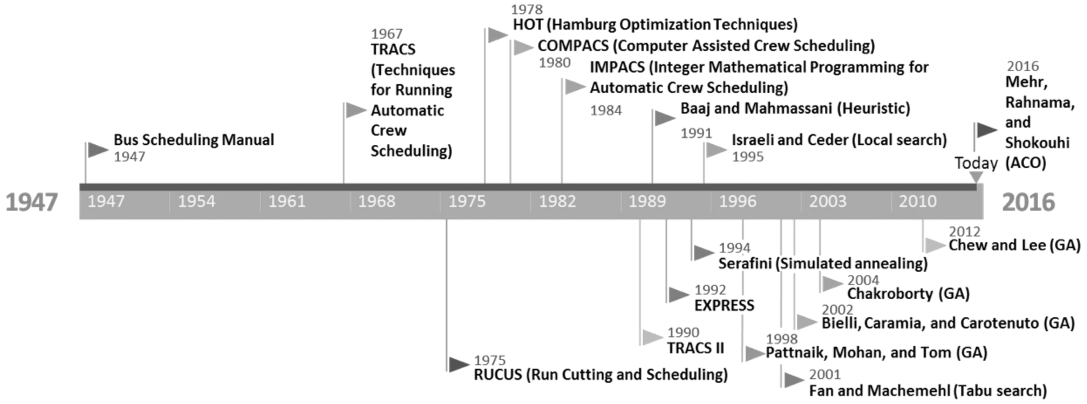

Fig 1 Timeline of evolution of operations research, about study of optimization problems associated with transportation systems.

A. Problem description

The VTSP models a realistic scenario, where a set of vehicles of different types are assigned to the trips required to cover a defined route. The optimization problem is to find an appropriate distribution of vehicles, with the goal of simultaneously maximizes two important objectives for users: the perceived delay to board the vehicle (waiting time) and the comfort associate to load factor, i.e. number of passengers on board.

This model considers steps, proposes by Ceder [6].

- Assume that the problem network route design (first step) was solved, therefore it has a defined route with their stops.
- Must have a passenger demand (load profile) for each timeslot in every stop.
- Unsatisfied demand (NSD) defines the amount of passenger that cannot be moved satisfactory, which implies more waiting time and congestion in the selected vehicles to cover the route in this time-period.
- The cost for each vehicle-trip include the cost of driver, energy consumption and vehicle maintenance.

B. Mathematical formulation

Our problem formulation is presented below. Given the following elements: A set of vehicle $B = \{b_1, \dots, b_n\}$, where b_i shows the number of vehicles of type i, where n is the number of different types of vehicles and $\sum_{i=1}^{n} b_i$ is the total fleet. S is a set of required trips $S = \{s_1, \dots, s_m\}$ of a defined route R.

The VTSP is based on two objective functions C_T and NSD_j :

$$\text{Minimize } \mathrm{C_T} = \sum_{i=1}^{n} \omega_i \text{ and } \mathrm{NSD_j} = \sum_{p \in R} \mathrm{LQ_p}$$

subject to:

$$f_j \geq f_{min},\ LF_{ij} = \frac{Q_{max}}{CAP_i * f_j} \leq LF_{max},$$

$$LQ_p = \max\left(Q_{j,p} - \sum_{i \in M_j} LF_{ij} * CAP_i, 0\right),\ \omega_i = c_i m_i,$$

$$c_i = c_i^{bus} + c_i^{gas} + c_i^{driver}$$

where:

c_i^{bus}	: Cost of maintenance and operation of vehicle.
c_i^{gas}	: Cost of fuel for each vehicle.
c_i^{driver}	: Cost hourly pay of the driver.
c_i	: Total cost of use of vehicle-type i.
m_i	: Number of vehicles-type i covering trips on S.
ω_i	: Cost of use vehicles of type i to cover trips of S.
C_T	: Total cost to use the fleet to cover all trips.
Q_{max}	: Maximum number of passengers at any stop.
$Q_{j,p}$	: Number of passengers of stop p on the route R.
CAP_i	: Capacity of a vehicle (number of seats plus the maximum allowable standees) from type i.
f_j	: Frequency for the period j.
f_{min}	: Minimum frequency.
LF_{ij}	: Load factor for the period j.
LF_{max}	: Maximum load factor for the period j.
ℓ_p	: Distance between the stop for p and p-1.
NSD_j	: Unsatisfied demand for a period j.
LQ_p	: Demand for passengers at the stop p that exceed the vehicle capacity.
M_j	: Set of vehicles used during the period j.

IV. Multiobjective Evolutionary Algorithms

The problem tackled in this paper are composed of two contradictory objectives that have to be optimized at the same time, so it belongs to the area known as multiobjective optimization (MOP). MOP consists of k objectives reflected in the k objective functions, $m + p$ constraints on the objective functions and n decision variables. The set of all the values satisfying the constraints defines the feasible region (or solution space) S and any point $x \in S$ is a feasible solution.

Solving a MOP can be viewed as the process of finding the set of solutions that dominate every other point in the solution space. This means that the solutions in that set are Pareto optimal for that problem, this is the so-called Pareto optimal set, or simply Pareto set. Each vector in the Pareto optimal set has a correspondence in objective function space, leading to the so-called Pareto front.

The main objective of multiobjective optimization algorithms is to obtain an approximation of the true Pareto front of a given MOP. In general, MOPs can have a Pareto front composed by a huge (possibly infinite) number of solutions. When using stochastic techniques, such as metaheuristics (e.g. evolutionary algorithms or simulated annealing), the goal is to obtain a Pareto front approximation (also called approximation set), i.e., a subset of solutions that represents the true Pareto front.

A. Evolutionary algorithms and MOCell

Evolutionary algorithms (EAs) are nature-inspired search strategies based on natural selection of evolution. They are non-deterministic methods used to solve MOPs due to their ability to find several solutions in one single run. The multiobjective EAs (MOEAs) are designed taking into account two features at the same time: satisfactory convergence and diversity properties. This means that they not only seek to find the approximate Pareto front, with a high degree of convergence, but also the Pareto optimal solutions must be evenly distributed along the Pareto front.

In this work, we focus on the cellular model of GAs (cGAs), particularly, on MOCell [16]. The main feature of this type of algorithms is that each solution belongs to a cell and can only recombined with a reduce number of solutions (neighboring cells). The main idea of this limitation is to perform a greater exploration of the search space. It maintains an external archive to store non-dominated solutions that is bounded and uses the crowding distance of NSGA-II to maintain a diverse set of solutions [17].

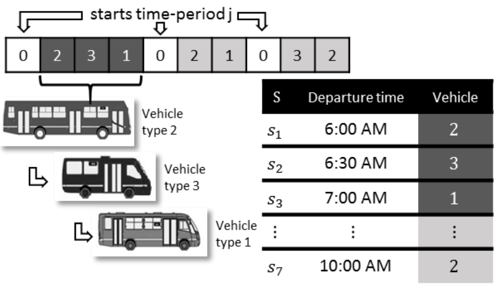

Fig 2. Example of solution representation for the VTSP

B. Encoding and solution representation

Solutions are encoded as arrays of integers, representing the vehicle-type assigned to cover a trip of S. Zeros mark new time-periods. The order of departures is specified in the sequence. Figure 2 shows an example of solution encoding for an instance with 3 different type of vehicles, 7 trips $s_k \in S$, and 3 periods of time of one hour.

The array size are taken from prior demand study and preliminary frequency determination. The distribution of zeros can be changed but cannot be consecutive and every time-period j has a same length and depends on total travel time to cover the route R.

C. Evolutionary operators

Population initialization: the population is generated by randomly assigning different types of vehicles to each departure and distributed in a toroidal grid of 10x10.

Selection: a tournament selection (tournament size: 8 individuals) to select the parents in a neighborhood of a study individual in the (x, y) position.

Recombination: a classic crossover technique of recombination is used, because it preserves the order in a good solution and encourages elitism.

Mutation: we use two type of mutations; swap and IFD. Swap mutation selects a randomly a set of vehicles and exchanges them. In IFD mutation (increase frequency departures), the number of vehicles defined in a time-period j is modified with the goal to improve the quality of service using more vehicles that can transport passengers.

V. Conclusions

In this paper, we have studied the multiobjective VTSP. The problem has been formulates considering two conflicting objectives: reduce the operational cost and maximize the quality of service for users. After describing the problem formulation in details and presenting the chosen algorithm, we explain a method to solve VTSP with our algorithm based on MOCell because it is a very competitive technique for solve MOP. The main lines of future work include calculate a crew scheduling to the chosen solution and adding real-time traffic information to improve the assignation of vehicles and generate and adaptive schedule for each period of time.

VI. Acknowledgements.

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