Multiobjective Optimization of Urban Public Transport Using MOCell

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Abstract. 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. Each city has different issues, authorities and responsible agencies of the mobility. However, they 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. In this paper, we study the problem of vehicle scheduling in urban public transport systems taking into account the vehicle-type (different capacity and operating cost) known as VTSP. It is modeled as a multiobjective optimization problem (MOP). We propose a heuristic based on MOCell (Multi-Objective Cellular evolutionary algorithm) to solve the problem taking into account restrictions of government agencies in context of smart cities to improve the Intelligent Transport Systems (ITS). The main objectives of ITS are: improve the safety, increase efficiency and capacity, reduce gasoline consumption and negative environmental impact, enhance economic productivity for users and providers, enhance the personal mobility, connivance, and comfort. The ITS has conflicting goals due to the provider is seeking to minimize the operating cost, and user want and expect a better service. A set of non-dominated solutions represents different assignments of vehicles to cover trips of a specific route. Then, a solution of our algorithm for VTSP proposes a distribution of vehicles in a schedule to reduce the cost, and guarantee the quality of service.

Keywords: Evolutionary algorithms, multiobjective optimization, public transport, smart cities.

1 Introduction

In increasingly interconnected and globalized world, more than half the population (54%) are located in urban areas, unlike 30% in 1950 [1]. This abrupt growth implies deep changes in size and distribution of space. 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 in urban mobility are often related to the inability of public transport systems to supply needs of a growing number of users [2]. 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. This paper presents a heuristic based on multiobjective cellular evolutionary algorithm

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(MOCell) [3] to solve the vehicle-type scheduling problem (VTSP), a variant of the vehicle scheduling problem.

2 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 [4]. The optimization problem is to find an appropriate distribution of different type of vehicles, with the goal of simultaneously minimize 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. Unsatisfied demand (f_2) defines the amount of passengers that cannot be moved satisfactory, which implies more waiting time and overload in the selected vehicles to cover the route in this timeslot. The cost for each vehicle-trip include the cost of driver, energy consumption and vehicle maintenance (f_1).

Our problem formulation is presented below: 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 f_1 and f_2 :
Minimize $f_1 = \sum_{i=1}^{n} \omega_i$ and $f_2 = \sum_{p \in R} LQ_p$, subject to: $c_i = c_i^{bus} + c_i^{gas} + c_i^{driver}$, $\omega_i = c_i m_i$, $f_j \geq f_{min}$, $LF_{ij} = \frac{Q_{max}}{CAP_i * f_j} \leq LF_{max}$, $LQ_p = \max\left(Q_{j,p} - \sum_{i \in M_j} LF_{ij} * CAP_i, 0\right)$,

where:

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

3 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. In this work, we focus on the cellular model of GAs (cGAs), particularly, on MOCell [3]. 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 in a toroidal grid). 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 [5].

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 1 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 is 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.

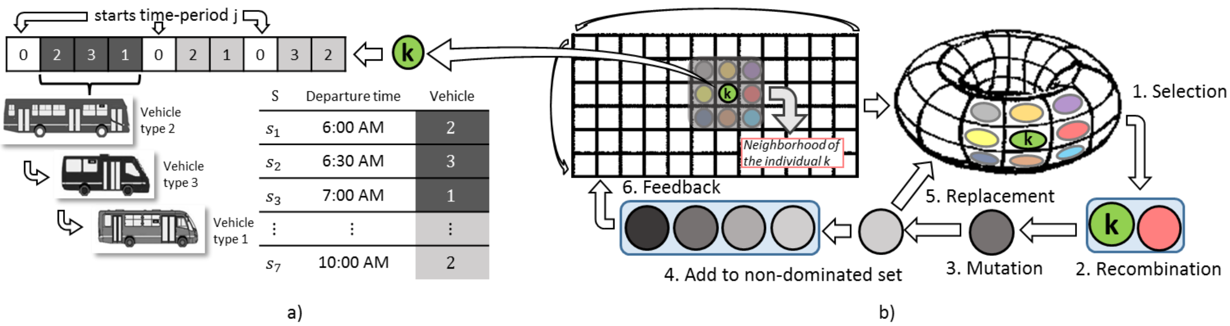

Fig. 1. a) Example of solution representation for the VTSP, b) Reproduction steps in MOCell

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 swap mutation selects a randomly a set of vehicles and exchanges them.

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