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A clonal selection algorithm for urban bus vehicle scheduling

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ABSTRACT

The bus vehicle scheduling problem addresses the task of assigning vehicles to cover the trips in a timetable. In this paper, a clonal selection algorithm based vehicle scheduling approach is proposed to quickly generate satisfactory solutions for large-scale bus scheduling problems. Firstly, a set of vehicle blocks (consecutive trips by one bus) is generated based on the maximal wait time between any two adjacent trips. Then a subset of blocks is constructed by the clonal selection algorithm to produce an initial vehicle scheduling solution. Finally, two heuristics adjust the departure times of vehicles to further improve the solution. The proposed approach is evaluated using a real-world vehicle scheduling problem from the bus company of Nanjing, China. Experimental results show that the proposed approach can generate satisfactory scheduling solutions within 1 min.

1. Introduction

Public-transport operations consist of four phases in sequence, namely network design, timetabling, vehicle scheduling and crew scheduling. Each of these phases can be treated as an independent problem.

The vehicle scheduling problem of an urban public-transport system is to assign vehicles according to a given timetable, making departure times coincide with start times in the timetable, as well as minimizing some objectives, such as the number of vehicles used. Such scheduling is very significant for bus companies since good schedules can reduce operation costs and improve quality of service.

Generally speaking, there are two types of bus vehicle scheduling algorithms, i.e., exact algorithms and heuristic algorithms. Exact algorithms, such as mathematical programming, obtain an optimal schedule but the computation time grows unmanageable with the size of bus fleet. Freling et al. [1] used a linear programming model to describe the single depot vehicle scheduling problem and proposed an auction based algorithm to solve it. Ribeiro et al. [2] presented a column generation approach to solve the vehicle scheduling problem. Kliewer et al. [3] utilized a time–space network to model the multi-depot vehicle scheduling problem. Heuristic algorithms, such as dispatching rules or Lagrangian relaxation, can get approximate scheduling solutions within reasonable computation time. Pepin et al. [4] summarized five heuristic algorithms for the multi-depot vehicle scheduling problem, namely branch-and-cut method, Lagrangian heuristic, column generation heuristic, large neighborhood search heuristic and tabu search. These approaches were applied to real-world data and their advantages and disadvantages were discussed. Freling et al. [5] proposed a rule-based heuristic algorithm to solve vehicle scheduling problems with different vehicle types. Laurent et al. [6] combined an iterated local search algorithm with a neighborhood schema for the multiple depot vehicle scheduling problem. Vanitchakornpong et al. [7] proposed a bus fleet scheduling model with multi-depot and line change operations and developed a constrained local search method to solve this problem. Ceder [8] proposed a heuristic algorithm based on the deficit function theory for multiple vehicle-type scheduling problems. Hadjar et al. [9] used a branch and price approach to solve the multiple depot vehicle scheduling problem with time windows.

Some studies investigated the integration of vehicle scheduling and crew scheduling. Huisman et al. [10] combined column generation with Lagrangian relaxation to solve single depot integrated vehicle and crew scheduling. They also used a similar approach to solve multi-depot cases. Haase et al. [11] presented a set partitioning model for the crew scheduling problem. The model contains side constraints on the number of vehicles in order to generate feasible vehicle scheduling in polynomial time. de Groot et al. [12] split large vehicle and crew scheduling instances into smaller ones and solve them in integrated or sequential approaches respectively using a Lagrangian relaxation algorithm. Laurent et al. [13] used a greedy randomized adaptive search procedure (GRASP) to

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solve vehicle and crew scheduling problems for the single depot case. Initial solutions were constructed using constraint programming techniques and then improved by a local search approach which embeds a neighborhood exploration mechanism. Rodrigues et al. [14] used conventional integer programming combined with a heuristic to solve vehicle and crew scheduling problems. Trip durations were stretched so as to provide a chance to adjust the trip departure times in the later phase to improve the final solution. Lin et al. [15] presented a multi-objective programming model of vehicle and crew scheduling problems, and used a branch and bound algorithm to solve it. Mesquitaa et al. [16] combined a multi-commodity model with a set partitioning/covering model to describe and solve the vehicle and crew scheduling problem.

An evolutionary algorithm (EA) is a kind of population based meta-heuristic. It starts from an initial population, and evolves the population by evolutionary operators until reaches a stopping criterion. Compared with traditional optimization algorithms, it can achieve global search capability and can effectively balance solution quality and computational time. Studies have shown that EA is very effective for NP-hard scheduling problems that cannot be solved by traditional algorithms within a reasonable timeframe [17–20]. Although EA has been used to solve vehicle routing problems [21,22], it has not been applied to solve realistic cases of urban bus vehicle scheduling.

Immune evolutionary algorithms emerged in recent years are inspired by the biological immune system, and have been applied successfully to a variety of optimization problems. Many researchers have shown that immune algorithms possess several attractive properties to avoid premature convergence and improve local search [23–25]. In our previous work [26], a culture immune algorithm was used to solve a small-scale bus vehicle scheduling problem. However, this approach was overly complex and only able to produce a feasible scheduling solution for a small-scale problem. We now propose an immune algorithm based vehicle scheduling approach to generate a practical and high quality vehicle scheduling scheme for a large-scale bus line scheduling problem in China.

In our approach, firstly, a set of vehicle blocks is generated based on the maximal wait time of bus drivers. A vehicle block is a set of consecutive trips by a single bus. Secondly, a subset of blocks is constructed by the clonal selection algorithm to produce an initial vehicle scheduling solution. Thirdly, two heuristics adjust the departure times of vehicles to further improve the solution.

The contributions of this paper includes: (1) a clonal selection algorithm based bus vehicle scheduling approach able to produce a good scheduling solution quickly (within 1 min); (2) a fitness function to evaluate the quality of a scheduling solution; (3) two heuristics to further improve the quality of the scheduling solution.

The remainder of this paper is organized as follows. The vehicle scheduling problem of urban bus lines is described in Section 2. Section 3 gives the proposed approach for this problem. In Section 4, results obtained by executing the approach on a real-world vehicle scheduling problem are given. Finally, concluding remarks are in Section 5.

2. Vehicle scheduling problem of urban bus lines

A bus line involving two control points is a typical case in practice, such that we consider a line with two control points ($CP1$ and $CP2$). In each of the two CPs, drivers can rest. A trip is the act of driving the vehicle between two CPs. Each trip has a duration and direction, starting from one CP to another. A vehicle block is a sequence of consecutive trips designated to one vehicle.

The initial departure time of a block means the departure time of its first trip. The timetable of a bus line consists of a large number of start times, each of which represents a trip. Given a timetable, the vehicle scheduling problem is to find a set of trips covering all start times (trips) in the timetable.

A constraint-based formulation of this vehicle scheduling problem is given as follows.

Let T be the set of trips in the timetable in chronological order. Let V be the set of vehicles and E be the set of drivers. For each driver $e \in E$, Sp_e represents the driver's maximum allowed spread time, which consists of the driver's working and resting time, and Wk_e is defined as the driver's maximum allowed working time.

Generally speaking, there are two types of blocks, namely long blocks and short blocks. A long block is completed by two drivers while a short block uses only one driver. The operation times of a short block and a long block can be denoted by Sp_e and $2Sp_e$, respectively. Let B^s and B^l be the set of short blocks and long blocks, respectively. For each block $b \in B^s \cup B^l$, $Tb(b)$ is defined as the set of trips that are covered by it.

For each driver $e \in E$, $Td(e)$ is defined as the set of trips that are assigned to the driver e. For each vehicle $v \in V$, $Tv(v)$ is defined as the set of trips that are assigned to vehicle v. For each trip $t \in T$, $st(t)$ and $et(t)$ represent the start time and end time of t, respectively. Let T_m be a set of time points and each element in it represents 1 min of a day.

In addition, we define

$$f(v,t)=\begin{cases}1, & t\in Tv(v)\\ 0, & t\notin Tv(v)\end{cases},\quad \forall v\in V,\quad t\in T$$

$$g_{CP1}(v,\delta)=\begin{cases}1, & \text{vehicle } v \text{ is stationed at } CP1 \text{ at time } \delta\\ 0, & \text{vehicle } v \text{ is not stationed at } CP1 \text{ at time } \delta\end{cases}\quad \forall v\in V,\quad \forall\delta\in T_m$$

$$g_{CP2}\left(v,\delta\right)=\begin{cases}1, & \text{vehicle } v \text{ is stationed at } CP2 \text{ at time } \delta\\ 0, & \text{vehicle } v \text{ is not stationed at } CP2 \text{ at time } \delta\end{cases}\quad \forall v\in V,\quad \forall\delta\in T_m$$

In order to assure service quality of the bus company, the following restrictions need to be satisfied:

(1) Each trip must be serviced by one vehicle.

$$\sum_{v\in V} f(v,t)\geq 1,\quad \forall t\in T$$

(2) The driver's spread time cannot exceed the allowed maximal spread time.

$$\left|st(t_1)-et(t_2)\right| < Sp_e,\quad \forall t_1\in Td(e),\quad t_2\in Td(e)$$

(3) The driver's working time cannot exceed the allowed maximal working time.

$$\sum_{t\in Td(e)} \left|st(t)-et(t)\right| < Wk_e,\quad \forall e\in E$$

(4) Trips that are assigned to each driver and vehicle must be feasible.

$$et(t_1)<st(t_2)\ \text{ or }\ et(t_2)<st(t_1),\quad \forall t_1\in Td(e),\quad t_2\in Td(e)$$

$$et(t_1)<st(t_2)\ \text{ or }\ et(t_2)<st(t_1),\quad \forall t_1\in Tv(v),\quad t_2\in Tv(v)$$