A Genetic Algorithm based Column Generation Method for Multi-Depot Electric Bus Vehicle Scheduling

Congcong Guo
School of Cyberspace Security
Beijing University of Posts and Telecommunications
Beijing China
18813172973@163.com

Chunlu Wang
School of Cyberspace Security
Beijing University of Posts and Telecommunications
Beijing China
wangcl@bupt.edu.cn

Xingquan Zuo
School of Computer Science
Beijing University of Posts and Telecommunications
Beijing China
zuoxq@bupt.edu.cn

ABSTRACT

In this paper, we study a multi-depot electric bus vehicle scheduling problem (MD-EVSP) and propose a genetic algorithm based column generation approach (GA-CG) for it. In GA-CG, a column refers to a driving plan of a vehicle. CG first generates a set of candidate columns. Then, a GA is used to select a subset of candidate columns from the column set to form the final solution. Experiments show that GA-CG can effectively solve MD-EVSP and runs much fast than branch and price algorithm.

CCS CONCEPTS

• Mathematics of computing → Combinatorial optimization; • Computing methodologies → Planning and scheduling; • Applied computing → Operation research;

KEYWORDS

Bus Scheduling, Electric Vehicle Scheduling, Column Generation, Genetic Algorithm

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1 INTRODUCTION

Bus vehicle scheduling is very vital to reduce operating cost of bus companies and ensure the quality of service. Recently, bus companies are using more and more electric vehicles due to their low transportation cost and low noise. Although there exist lots of literature on bus vehicle scheduling [1], there still lack studies on electric bus vehicle scheduling problem (EVSP). Multi-depot bus vehicle scheduling is significant because it can share vehicles among multiple bus lines to balance their carrying capacities at different time periods.

In this paper, we study MD-EVSP and propose a genetic algorithm based column generation method to quickly generate high quality solutions to MD-EVSP. First, initial columns are created by a heuristic method and added into the column set. Then, a label connection method is used to add new columns into the column set. Finally, a genetic algorithm (GA) is devised to select partial columns from the column set to construct a final solution.

2 PROPOSED SOLUTION APPROACH

MD-EVSP has multiple depots and bus lines. Each bus line has two control points, each of which has a departure timetable. A trip of a vehicle covers a departure time in the timetable if the trip departs from the time. The problem is to schedule all used vehicles among the bus lines to make the trips of those vehicles cover all departure times in the timetables of those bus lines and meanwhile each departure time is not allowed to be covered by more than one trip.

The CG-GA consists of two parts. The first part generates a set of candidate columns *S* by the column generation method. In the second part, a genetic algorithm is used to select a subset of columns from the column set *S* to construct the final solution.

Good initial columns are important for the column generation method to achieve high quality candidate columns. Thus, we proposed a heuristic algorithm to generate initial columns and add them into the column set *S*.

The first part of CG-GA is to generate new columns and add them into *S*. MD-EVSP is decomposed into a primal problem and a subproblem according to the decomposition principle [3]. The subproblem is a shortest path problem with resource limitation and its purpose is to generate a set of columns. A column represents a vehicle route in one day. The primal problem is a path-based set partition problem. It is not used to select a subset of columns but to provide the dual information. First, CPLEX is used to solve the relaxation of the integer programming model of the primal problem, obtaining the dual information of its optimal solution. The dual information is used to guide a label correction method [4-5] to solve the subproblem to find new valid columns and add those columns into *S*. Then, CPLEX is used to solve the relaxation model of the primal problem (in this case, the problem is to find a subset of columns from the updated *S*) again to find the dual information, which guides the label correction method to add more new columns to *S*. Repeat above procedure until CPLEX cannot find a better optimal solution for the relaxation model of the primal problem within a given number of consecutive iterations.

The second part is to select a subset of columns by a GA. A coding scheme is devised. An individual Z represents a set of columns and is encoded as a binary coding $\{z_1, z_2, \ldots, z_{|n|}\}$, where n is the number of columns (vehicles) in the set S. Each gene corresponds to a column (a vehicle route). $z_i = 1(0)$ means that the ith column in S is (not) belongs to the individual (solution). A population includes a number of individuals. First, the population is initialized randomly. Each initial individual Z needs to meet $L_{min} \leq \sum_{i=0}^{|n|} z_i \leq L_{max}$ to avoid bad initial solutions. That is, the number of vehicles in each initial individual is restricted within $[L_{min}, L_{max}]$, where L_{min} and L_{max} are the estimated minimum and maximum used vehicles, respectively. After initialization, the population performs the roulette select, multi-point crossover and random mutation operations. An elite strategy is adopted to keep elite solutions. After the GA stops, the best individual in the population of the last generation is regarded as the final solution to MD-EVSP.

3 EXPERIMENT RESULTS

GA-CG is compared against branch-and-price (BP) algorithm. Experimental data comes from five bus lines in Beijing City, China. The combinations of those bus lines form 16 problem instances.

10 runs of GA-CG and BP are done for each problem instance. Experimental results are shown in Table 1. The third column shows the lower bound (LB) of the primal problem obtained by CPLEX. Results of BP are presented in columns 4-6 (the lowest cost, the mean cost and gap between the lowest cost and the lower bound). Results of GA-CG are presented in the following columns.

Table 1 shows GA-CG can find solutions with lower cost values for more problem instances compared to BP. For problem instances 1-8, GA-CG obtains better solutions (smaller gaps) for 3 instances and BP obtains the better solutions for 5 instances. For problem instances 9-16, GA-CG finds solutions with lower cost values (gaps) than BP for all instances except instance 11. Computational time of GA-CG is about 11-40 times shorter than that of BP.

Table 1: Comparison of CG-GA and BP.

Ins	Trips	CPLEX LB	BP			CG-GA		
			Lowest cost	Mean cost	Gap	Lowest cost	Mean cost	Gap
Ins 1	744	58907.2	60403.4	60639.1	**2.54%**	61723.4	62149.3	4.78%
Ins 2	894	77420.2	79069.3	79084.7	**0.52%**	83921.5	85534.8	8.39%
Ins 3	880	73473.4	75222.1	75648.2	**0.75%**	75868.9	75868.9	3.26%
Ins 4	872	81082.7	83223.3	83563.8	2.24%	81946.6	82036.2	**1.06%**
Ins 5	840	72083.8	73554.3	74001.2	2.04%	73487.9	76040.4	**1.95%**
Ins 6	766	64366.7	65235.7	65255.0	**1.43%**	65760.3	66293.3	2.17%
Ins 7	826	70043.8	71577.8	71949.0	2.92%	70713.7	70474.3	**0.96%**
Ins 8	758	65422.2	66449.3	66475.5	**1.57%**	68511.4	67731.5	4.72%
Ins 9	818	68072.1	72163.2	72183.7	6.01%	70626.7	73004.4	**3.75%**
Ins 10	954	80091.8	83792.0	83792.0	2.21%	81437.7	82459.8	**1.68%**
Ins 11	1086	98308.4	100038.6	100038.6	**2.28%**	104063.8	106616.0	5.85%
Ins 12	1146	97474.2	99287.2	99540.6	3.08%	98063.4	98063.4	**0.60%**
Ins 13	1072	86358.8	87308.8	87593.7	2.69%	86761.2	87948.8	**0.47%**
Ins 14	1064	92352.4	95224.6	95640.2	3.06%	92397.3	92481.0	**0.05%**
Ins 15	1200	104401.0	107773.2	107731.4	5.08%	106927.0	108583.0	**2.42%**
Ins 16	1392	120921.0	124161.7	124717.9	2.68%	121622.0	122737.0	**0.58%**

4 CONCLUSIONS

In this paper, we propose a genetic algorithm based column generation method (GA-CG) for a multi-depot electric bus vehicle scheduling problem (MD-EVSP). Experiments show that GA-CG can produce high quality solutions quickly. It is forty times faster than the branch-and-price algorithm, only taking several minutes.

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