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An Optimal Approach for Vehicle Scheduling

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Abstract

The transit-operation planning process commonly includes four basic activities: (1) network route design, (2) timetable development, (3) vehicle scheduling, and (4) crew scheduling. Generally speaking vehicle and crew scheduling are critical .The purpose of this work is to address the vehicle and the crew scheduling problem, while taking into account the interactive association between vehicle and crew. The quasi-assignment model and set-covering model will be applied in solving the problem .We propose new mathematical formulations and Lagrangian relaxation, and employing two-phase hybrid method for dealing with vehicle and crew scheduling problem. Genetic algorithm narrows down the solution space which consists of potential duties, and then yields some elite schedules. The objective is to minimize the sum of total vehicle and crew costs.

1. Introduction

The public-transport operation planning process commonly includes four basic activities: (1) network route design, (2) timetable development, (3) vehicle scheduling, and (4) crew scheduling (see Ceder, A., 2007). Public-transport operation planning is the core of public transport operation scheduling. In the transit operation planning process, the vehicle and crew scheduling problem is the critical for the public transportation enterprises to save the resource. So it is important to recognize that significant savings in resources can be made by reorganization of bus routes and frequency to suit the actual travel demand which can minimize the fleet size. In this paper, transit bus vehicle and crew scheduling problem is formulated and solved in two phases. In the first level, this paper addresses the vehicle and crew scheduling problem, respectively. In the second phase, an attempt is made to further reduce the fleet size and genetic algorithms are used as an optimization tool. Genetic Algorithm can

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solves this model (see Beasley, J.E. / Chu, P.C. (1996)).They could be effective in narrowing down the solution space which consist of potential duties, and yield some elite schedules.

The work is organized as follow. The first is introductory section. The second part covers a literature review and the third part introduces Approach for solving Scheduling of the problem. The fourth part, we effectively use the genetic algorithm to narrow down the solution space. The final part is a concluding remark.

2. Literature review

IPv6 l$\ddot{o}$bel (1998) discussed the multiple-depot vehicle scheduling problem and its relaxation into a linear programming formulation that can be tackled using the branch-and-cut method. A special multi-commodity flow formulation is presented, which, unlike most other such formulations, is not arc-oriented. A column-generation solution technique is developed, called Lagrangean pricing; it is based on two different Lagrangean relaxations. Heuristics are used within the procedure to determine the upper and lower bounds of the solution, but the final solution is proved to be the real optimum.

Frelingetal discussed the case of single-depot with identical vehicles, concentrating on quasi-assignment formulations and auction algorithms. A quasi-assignment is a reduced-size, linear problem in which some of the nodes and their corresponding arcs are not considered. An auction algorithm is an iterative procedure in which neither the primal nor the dual costs are obliged to show an improvement.

Haghani et al. (2003) compared three vehicle scheduling models: one multiple-depot presented by Haghani and Banihashemi (2002) and two single-depot formulations which are special cases of the multiple-depot problem. The analysis showed that a single-depot vehicle scheduling model performed better under certain conditions. A sensitivity analysis with respect to some important parameters is also performed; the results indicated that the travel speed in the DH trip was a very influential parameter [4].

Huisman et al. (2004) proposed a dynamic formulation of the multi-depot vehicle scheduling problem The traditional,static vehicle scheduling problem assumes that travel times are a fixed input that enters the solution procedure only once; the dynamic formulation relaxes this assumption by solving a sequence of optimization problems for shorter periods. The dynamic approach enables an analysis based on other objectives except for the traditional minimization of the number of vehicles; that is, by minimizing the number of trips starting late and minimizing the overall cost of delays. The authors showed that a solution that required only a slight increase in the number of vehicles could also satisfy the minimum late starts and minimum delay-cost objectives.

3. Clew of Integrated Approach for Scheduling

3.1 Background on the integrated approach

Timetable formulation needs to meet certain service level .meanwhile, we should consider vehicle and crew scheduling based on the timetable will bring many benefits to the company, which often depends on the company's decision. Interactions of the vehicle scheduling and crew scheduling is obvious. A certain vehicle scheduling tends to increase some restrictions to the crew scheduling problem, and vice versa (see Banihashemi, M., Haghani, A., (2000)). Vehicle scheduling is more flexible, and solve the crew scheduling problem should consider certain constraints, so using the Sequential approach to

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solve the two questions is not reasonable. These constraints include:

- ●Halfway transfer that can not be allowed;
- ●each task is assigned to one duty
- ●Stop waiting vehicles must be someone on duty
- ●maximum working time without a break
- ●the cost of a duty is a combination of fixed costs (e g. wages and overtime payment)
- ●a sequence of tasks cannot be broken that can be performed by a single crew member without interruption.

Quasi-assignment model can solve the vehicles scheduling problem, and the set partitioning model can solve crew scheduling problem. Quasi-assignment model ensure the feasibility of the vehicle scheduling, while in the set covering model of the CSP, the objective is to select a minimum cost set of feasible duties such that each task is included in at least one of these duties [7].

The quasi-assignment model and the set covering model with additional constraints can be formulated as follows:

$$L(\lambda,\mu) = L_x(\lambda,\mu) + L_y(\mu) + \sum_{p\in I_1} \lambda_p \quad ,$$

$$L_x(\lambda,\mu) = \min \sum_{k\in K} \bar{d}_k x_k \quad ,$$

$$x_k \in \{0,1\} \forall k \in K \quad ,$$

$$L_y(\mu) = \min \sum_{k\in K} \bar{c}_{ij} y_{ij} \quad ,$$

$$\sum_{\{n:(m,n)\in A\}} y_{mn} = 1, \forall n \in N \quad ,$$

$$\sum_{\{m:(m,n)\in A\}} y_{mn} = 1, \forall m \in N \quad ,$$

$$y_{mn} \in \{0,1\}, \forall (m,n) \in A \quad ,$$

$$\bar{c}_{mn} = c_{mn} + \mu_{mn}, \forall (m,n) \in A \quad ,$$

$$\bar{d}_k = d_k - \sum_{p\in I_1(k)} \lambda_p - \sum_{(m,n)\in A(k)} \mu_{mn} \quad ,$$

$\bar{d}_k$ is the reduced cost of the duty k.

$\bar{c}_{mn}$ is the reduced cost of the deadhead from m to n.

I1(k)-A collection of passenger driving section that in the k

A(k)-The collection of non-passenger driving section that in the k

We use two-phase hybrid method to solve the LaGrange dual problem approximately; we can not only get a good lower bound, but also obtain a final set of Lagrange multipliers.

3.2 Two-Phase hybrid method

Parameter Two-phase hybrid method combines the subgradient method in a first phase, and constraint generation is a second phase. The multipliers are first adjusted according to the subgradient formula, and at the same time constraints corresponding to all known solutions of the Lagrangean subproblems are added to the LP master problem. The value of the LP master problem is taken as the current estimate of the optimum of the Lagrangean dual. This estimate gets more and more accurate as iterations go by, so there is no need for any adjustment of the step size; The Lagrangean relaxation bound and the value of the master problem provide a bracket on the dual optimum, and this yields a convergence test, like for the pure constraint generation method. One must make sure that the process does not cycle .If constraints get repeated, the masters problem cannot improve. After the same cut has been generated a given number of times (about 5 times), one can switch to a pure constraint generation phase.

We compute the lower bound with respect to these initial set as follows. We associate nonnegative Lagrangean multipliers λ(λ1, λ2, λ3,⋯, λi) with the constraints and then the

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remaining Lagrangean subproblems are added to the LP master problem. We stop if there are no duties left with negative reduced cost or if the lower bound obtained by the subgradient optimization does not significantly change for a number of iterations. Finally we compute a feasible solution by solving a set covering problem in which we consider all the feasible schedulings which have been generated along the way.

It is well known that it is difficult to generate a good set of columns at the beginning of the algorithm; the paper suggests using an initial phase that generates the "outside walls" of the Lagrangean function dome, to use a graphical explanation of the procedure. If one views the Lagrangean function as a dome in R, where Rm corresponds to the Lagrangean multipliers and R to the Lagrangean function, then in the initial phase, one will try to generate faces that together define a bounded polyhedron containing the Lagrangean dome. In the Figure 1, the three faces defined by the solid lines define a bounded polyhedron. The dotted lines define faces of the dome that may be discovered later in the algorithm. The initial phase uses a subgradient algorithm with large step size. Once the column generation master problem is feasible, or possibly some iteration later if one thinks there is some advantage in generating a few more faces, one switches to either constraint or column generation [8].

3.3 Genetic algorithm

Genetic Algorithm can solve a set covering model. They could be effective in narrowing down the solution space which consist of potential duties, and yield some elite schedules for the problem. The continuous solution provides two pieces of useful information. First, the sum of all xk is a very accurate estimation of the minimum number of shifts required in the integer solution. It is rounded up if the fractional part is non-zero. Second, it is a general property of LP's that the continuous solution will involve a (relatively small) number of shifts that is no more than the total number of work pieces. The corresponding variables for some of these shifts may have values of one, but most of them will have fractional values. GAs work with many schedules in each generation and therefore can gather a lot more information.

3.3.1 The Chromosome representation

As we all know, the bus driver scheduling problem is basically composed of two types of information: the set of candidate duties and the set of pieces-of-work. In general, there are much more duties than pieces-of-work, but each solution is composed of a relatively small number of duties. The chromosome structure is commonly used 0-1integer variables with fixed length, where each gene is related with a duty, and its value is represented by one or zero, according to the presence or absence of the duty in the solution. This coding scheme makes the chromosome structures simple, and obviously easy to manipulate by the standard operators, but sometimes the resulting solutions are no longer guaranteed to be feasible. We can apply a penalty function to penalize the fitness of infeasible solutions, or design heuristic operators which transform infeasible solutions into feasible solutions.

For example, if for a given problem we have 15 candidate duties and a solution is composed by duties 1, 3, 4, 11,13 and 14, the corresponding chromosome can be represent as follows.

Table 1 Column gene string

1	2	3	4	5	…	11	12	13	14
1	0	1	1	0	0	1	0	1	1

We propose a pieces-of-work (the daily work of each vehicle is divided into units, called pieces-of-work) coding scheme, associating the two

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fundamental types of information contained in a solution: the duties and the set of pieces-of-work [7]. Each piece-of-work corresponds to a gene of the chromosome, and each gene is characterized by the duty that covers the piece-of-work in that particular solution. The genes are ordered by bus and for each bus they are ordered by time.

It represents a solution for a problem with 10 pieces-of-work. In the followed table2, the value of each gene corresponds to the duty that covers the piece-of-work. For example the duty 4 covers pieces-of-work 2 and 9). For the uncovered pieces-of-work, it will be given the value 0.

Table 2 Row gene string

1	2	3	4	5	6	7	8	9	10
1	4	3	0	2	5	4	6	2	3

Genetic Algorithm solves a set covering model, and we can use the followed coding scheme.

Table 3 Coding scheme

aij	duty i				
pieces-of-work j	1	0	0	0	1
	0	1	0	0	1
	0	1	1	0	0
	1	0	1	0	1
	0	0	1	0	0

aij =1, if the piece-of-work j belongs to duty i, otherwise aij =0.

I={i: duty},

P= {j: piece-of-work duty},

3.3.2 The fitness function

In practice, the bus crew scheduling problem involves some conflicting objectives. The sum of the individual costs is important in the solution. The cost of a duty s is computed as a function. In our genetic algorithm, the most important criteria used are the following:

(1) Total cost of the duties;

(2) Whether cover all the pieces-of-work those or not.

$$\text{Adaptability} = -\sum_{i=1}^{m}(f(D_i)+W)x_i - p\sum_{j}^{n} IF(\sum_{i}^{m} a_{ij}x_i - 1 \geq 0, 0, 1 - \sum_{i}^{m} a_{ij}x_i),$$

where f(Di) - the cost of the duty i, aij =1, if the piece-of-work j belongs to duty i, otherwise aij=0.

P: a large positive number.

w: the increased cost because of adding a driver.

We have described the important details about GA for solving the set covering problem. The GA also include Generation of the initial population, Parent selection scheme [8, 9], Crossover and Mutation, We can see these from Genetic algorithms for the bus driver scheduling problem or other papers.

4. Concluding remark

This work should based on data and algorithms, and can get the computational results for this approach which have advantage over sequential approach to solve vehicle and crew scheduling problem ,and then employing GA method to optimize the problem is feasible

In the transit-operation planning process, the approach to deal with vehicle and crew scheduling problem is critical. The objectives are to minimize the sum of total vehicle and crew costs and to realize the rational allocation of public transportation resources. The approach indicates that the computational algorithm gives a better result than the original algorithm. In the process, the cost of vehicle and crew can influence the computational result .it is more attractive to employ the computational approach, when the crew cost is

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higher than the vehicle cost.

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