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Research Article

Discrete Optimization Model and Algorithm for Driver Planning in Periodic Driver Routing Problem

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Workforce planning is an operation management problem in the delivery industry to improve service quality and reliability, and the working attitude and passion of drivers, as the direct implementors of delivery service, affect the service level. Consequently, assigning equal workload for drivers so as to improve drivers' acceptance is a reasonable and efficient workforce plan for managers. This paper investigates a periodic driver routing problem to explore the relationship between workload differential among drivers and total workload; the objective of the optimization problem is to minimize the total workload. To tackle this problem, we first propose a mixed-integer linear programming model, which can be solved by an off-the-shelf mixed-integer linear programming solver, and use the local branching based method to solve larger instances of the problem. Numerical experiments are conducted to validate the effectiveness and efficiency of the proposed model and solution method, as well as the effect of small workload differential among drivers on the total workload.

1. Introduction

With the fierce competition of the service industry and the change in consuming ways of people, most competitors realize that decreasing service cost is not advisable for the long-term development of companies. And service reliability and customer satisfaction can be more decisive for long-term performance of service industries. Figure 1 shows the process of making profits in the service industry; we can see that drivers' satisfaction is the essential factor for increasing companies' profit, its improvement can make drivers provide high-quality service, and these two factors can be controlled by companies. Moreover, the direct influence of providing high-quality service is improving the customers' satisfaction. When customers' satisfaction rises to a high level, companies can obtain the customers' loyalty and gain long-term profit. Consequently, drivers' satisfaction is the essential internal factor, and customers' satisfaction is the most direct and important external factor for gaining profit to companies.

For improving customers' satisfaction, many companies have adopted service consistency strategies, like service time consistency. For example, many families have a long-term demand for fresh milk. And milk distributors will deliver milk on a certain time every day; when the milk delivery time is regular, customers can predict the arrival time of milk every day and their satisfaction is improved. Moreover, the "vegetable basket" domestic project has developed to about 4000 wholesale markets for agricultural and sideline products in various provinces throughout the country. The whole country has initially formed a stable market system of "vegetable basket" which takes the central wholesale market as the core and links the production base with the retail market. In order to ensure the timely supply of vegetables and fresh products for customers, it is necessary to supply products regularly and distribute them to retail markets within a specified period of time. So we can see that the service time consistency is very important for meeting the customers daily demands.

In logistics companies, drivers are the critical executants of enhancing service quality and reliability. So, the management of drivers is critical for improving service quality. For example, the service pattern of UPS earns much concern of shipping industry in 2006; this company relies on its drivers, and the method of managing drivers is to work on the same routes to form a real bond with customers, which improves the service quality and maintains a high level of familiarity

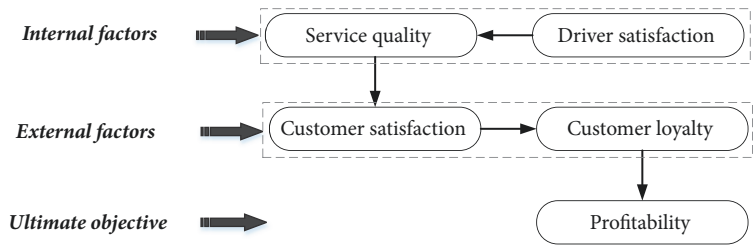

Figure 1: The process of making profits in the service industry.

of customers. Many domestic companies also adopt the routes consistency for drivers. For example, school buses and scheduled company buses should keep routes consistency to ensure service quality because the routes consistency can make drivers more familiar with the driving routes so as to decrease the probability of accidents. And for the small-package shipping companies, it is also necessary to keep routes consistency. For example, S.F. Express needs to deliver more than 1,000 biological products and more than 580,000 vaccines in batches to disease prevention control centers in Western cities. In order to ensure the timely and safe arrival of drug transportation, the strategy of routes consistency is adopted to improve the drivers' familiarity with the driving routes in order to cope with traffic emergencies.

From the perspective of drivers, the realization of high service quality and reliability depends on their working aspiration, which can be enhanced by the equitable workload that companies provide, e.g., maintaining the balanced workload among drivers per day and letting each driver visit the same customers over the period. In reality, many companies focus on achieving workload balance for employees, especially in the transportation industry. For example, some companies have early, mid, and late buses to pick up and deliver employees to and from work, so drivers have three working time shifts, with each time shift at different working time. Companies will maintain the differential of the total workload among drivers in three shifts within a small range when distributing the operated routes for drivers. What is more, drivers' working content is relatively single, which is mainly measured by driving time and service time, so maintaining the workload balance among drivers is important and practical.

Aiming to improve the service quality and reliability, this paper investigates a driver routing problem (DRP) by considering the workload balance of drivers in a planning period for small-package shipping companies. In the classic vehicle routing problem, many scholars have studied the workload balance by limiting the maximum length or travel time of a route, or minimizing the differential among the longest and shortest routes (see, e.g., Mourgaya and Vanderbeck [1], Carlsson et al. [2], and Narasimha et al. [3]). But in period vehicle routing problem, as shown in Figure 2, the demands of 11 customers in the planning period T=3 are denoted by d. We can see that, because of the different demands of the customers on each day, the operated routes by three drivers are different too from day 1 to day 3, which means there is a large differential in the workload among drivers over the whole period. In order to achieve fair workload assignment, which further enhances the acceptance of drivers, this paper proposes a new strategy; i.e., in the planning period, keep the workload among drivers at the same level. In other words, if the workload difference among drivers is small, the assignment of drivers' workload is fair and more acceptable for drivers. Moreover, the proposed constraints are more flexible to maintain the relationship among drivers, because each driver can obtain the same level of payment with small workload differential.

The remainder of this paper is organized as follows. Related work is reviewed in Section 2. We describe the problem and present its mathematical model in Section 3. In Section 4, a local branching based method is used to solve larger scale instances for this problem. Numerical results are reported and discussed in Section 5 which is followed by a conclusion in Section 6.

2. Literature Review

The problem studied in this paper is a period driver routing problem (PDRP), which belongs to an NP-hard problem (see, e.g., Zhen [4]; Zhen, Chew, and Lee [5]). And this problem is the extension of the vehicle routing problem. Other extension problems include dynamic vehicle routing problem and stochastic time-dependent vehicle routing problem (see, e.g., Xu, Pu, and Duan [6]; Sun, Duan, and Yang [7]). In order to improve customers' satisfaction, many small-package shipping companies focus on service consistency, which attracts scholars' attention as well. Groër, Golden, and Wasil [8] first propose the consistent VRP (ConVRP), which contains driver consistency and arrival time consistency. And an algorithm based on the record-to-record travel algorithm is developed. Kovacs, Parragh, and Hartl [9] present an efficient solution method which calls template-based adaptive large neighborhood search to solve the ConVRP. And in their next published paper, cooperating with Golden [10], they propose a generalized ConVRP (GenConVRP), which relaxes the consistent constraints of ConVRP. An approach based on a flexible large neighborhood search to the entire solution is applied. In addition, they make a survey of vehicle routing problems by considering the consistent service [11]. In 2015, Kovacs, Parragh, and Hartl [12] extend the GenConVRP to a multiobjective GenConVRP by considering several independent objectives. Two exact solution approaches are proposed to solve small scale instances, and large instances are solved

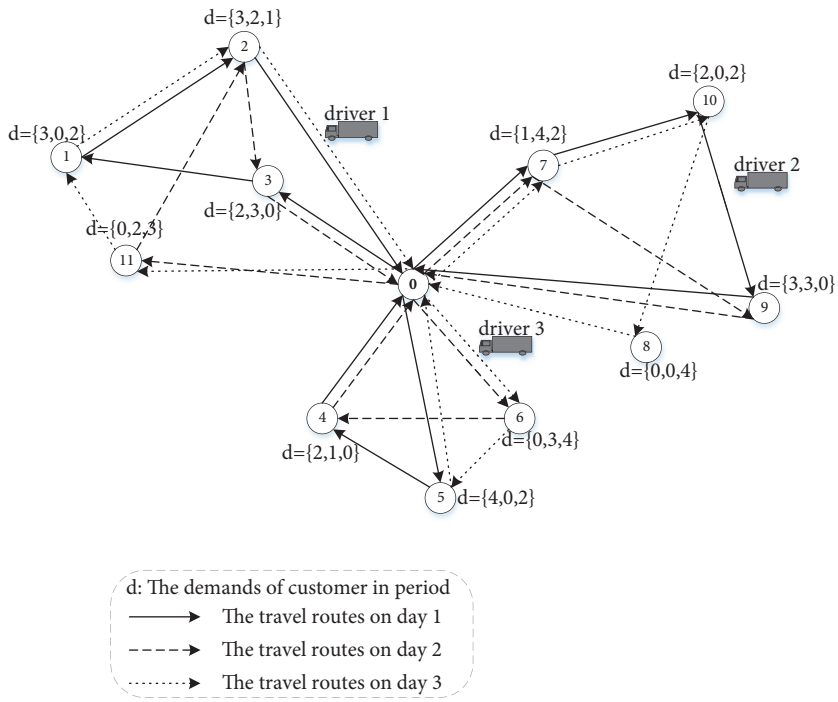

Figure 2: The operated routes by drivers in period.

by a heuristic which combines the multiple directional local search framework and large neighborhood search (LNS). In order to solve the same problem, Lian, Milburn and Rardin [13] develop an improved multiple directional local search (IMDLS) which makes use of the LNS to find improved solutions according to at least one objective to be added to the set of nondominated solutions at each iteration.

In other service industries, Macdonald, Dörner and Gandibleux [14] study the problem of consistent routing and scheduling for mobile nurses. The objective is minimizing the number of nurses assigned to one client. Nickel, Schröder, and Steeg [15] study short-term and mid-term home health nurse routing problems and use different heuristics combined with constraint programming strategy that aims to obtain flexible service consistency in treating different realistic constraints. Huang, Smilowitz, and Balcik [16] focus on the routing problem to assess damage and relief needs following a disaster. Campelo et. al [17] study the routes consistency of several warehouses to hundreds of orders. What should be mentioned is that the service consistency required the learning process and planning of drivers. Zhong, Hall, and Dessouky [18] study the construction of routes for local delivery of packages and create a two-stage vehicle routing model to balance the trade-offs between the vehicle dispatch consistency and the varying demand services. Coelho, Cordeau, and Laporte [19] introduce the concept of consistency in the inventory-routing problem (IRP) and discuss the situations with and without consistency requirements. And Coelho and Laporte [20] consider the consistency requirements in the multiproduct IRP and propose a branch-and-cut algorithm to solve it.

Other scholars, such as Francis, Smilowitz, and Tzur [21], Feillet et al. [22], Luo et al. [23], and Subramanyam and Gounaris [24], study PVRP with other different service consistency. Francis, Smilowitz, and Tzur [21] compare two delivery strategies for the PVRP: one is to visit each customer with his true demand, and the other is to visit each customer with his true demand or average demand, which is more flexible and consistent. The experiments indicate that cost can be decreased by adopting delivery consistency for some customers. Feillet et al. [22] define a multiday VRP called the time-consistent VRP considering the time consistency of the service. A large neighborhood search heuristic is used to solve the new problem. Luo et al. [23] investigate a PVRP with time windows and limited visiting quota. Subramanyam and Gounaris [24] develop three MIP formulations and use a class of valid inequalities to strengthen these formulations to solve the consistent traveling salesman problem.

In order to improve the service reliability, there are few studies which consider the workload balancing from a period view. Mourgaya and Vanderbeck [1] study the PVRP which aims to optimize the workload balance of each route and regional compactness of routes, and use a column generation procedure followed by a rounding heuristic to solve this problem. Gulczynski, Golden, and Wasil [25] develop a heuristic algorithm which combines the record-to-record travel algorithm with an integer program for the PVRP, and extend this heuristic algorithm to handle some real-world routing constraints such as balancing the workload of drivers and regenerating new routes. Smilowitz, Nowak, and Jiang [26] evaluate the effect

that balancing the visited customer and region for drivers has on routing costs and propose multiobjective PVRP models to balance the travel distance and driver planning.

In addition, a number of scholars have made research on the workload balancing in other VRP. Some of them aim to solve the capacitated VRP with route balancing, such as Borgulya [27], Jozefowiez, Semet, and Talbi [28], Oyola and Løkketangen [29], and Mandal et al. [30]. They study the capacitated VRP with two objectives; i.e., they aim to not only minimize the routing distance or cost, but also consider how to balance the workload of each route and propose different methods to solve this problem. Extension related to the capacitated VRP with workload balancing which considered the time window is also studied by few scholars (see, e.g., BañOs et al. [31], de Freitas Aquino and Arroyo [32], and Melián-Batista et al. [33]); all of them aim to not only minimize the total travel cost but also balance the distances traveled among vehicles and propose several heuristic methods to solve this problem. In the min–max VRP, the biggest difference from other VRP is that it considered the workload balancing as the primary objective by minimizing the longest distance or traveling time among routes. And different methods are proposed by scholars (see, e.g., Carlsson et al. [2], Narasimha et al. [3], Wang, Golden, and Wasil [34], Carlsson, Carlsson, and Devulapalli [35], and Schwarze and Voß [36]).

The applications related to workload balancing are also reported in some literature. Apte and Mason [37] use the route balancing concept to develop models and heuristics for library delivery operations. Liu, Chang, and Huang [38] study the VRP with the balanced workload and delivery time of vehicles and present a multiobjective zero-one MIP to solve the problem. Huang, Smilowitz, and Balcik [39] focus on the balanced service that recipients received in humanitarian relief operations. And they also consider the goals of minimum cost as well as the quick and sufficient distribution. Zhen [40] proposes the workload balancing protocol for mitigating congestion in the optimization of container ports.

Different from the above-mentioned methods, to improve service reliability, we require that the workload differential among drivers over the period is within a small range to enhance drivers' acceptance and satisfaction, so as to enhance the service quality eventually. The contribution of this paper is summarized as follows. Firstly, this paper proposed a new strategy from the drivers' perspective to improve service quality and reliability. Secondly, a new mixed-integer linear programming (MILP) to minimize the workload of drivers, by considering the workload balance of drivers, is proposed. Thirdly, in order to solve this problem on a larger scale, we use the local branching based method to accelerate the computational time and obtain better solutions in a reasonable time. Lastly, a sensitivity analysis is conducted to explore the effect of workload differential among drivers on the total workload.

3. Problem Description and Model Formulation

The problem in this paper is a PDRP, so the basic background of PDRP is introduced in this section. In addition, the constraints concerning the workload balance are also given in this section. Lastly, a model formulation is presented. Different from the traditional PVRP, the problem we study is a PDRP with considering the workload balance of drivers, which aims to minimize the total workload over the period with small maximum workload differential among drivers. The workload of drivers is measured by travel time and service time.

In the standard PDRP, there is a single depot, with a homogeneous fleet departure from the single depot to serve set of customers in the planning period, and each customer has a specific demand request per day. Drivers should go back to the single depot after finishing service requirements. Each driver visits a series of customers with a limited capacity and limited travel time, and each customer cannot be visited by more than one driver each day. What should be mentioned is that the situation of a driver with no workload in one day is allowable. In order to achieve service quality and reliability, the consideration of workload balance for drivers is summarized as follows.

Keeping balanced workloads for drivers is propitious to increase the drivers' working passion and acceptance of the work schedule. Consequently, drivers' service quality and reliability are improved. The periodic workloads in this paper are measured by the total traveled time and service time during the whole planning period. The balanced strategy is setting a value of workloads' difference among drivers (denoted by Θ); i.e., the maximal workloads' difference among drivers is no more than Θ. In this way, not only the service quality is improved, but also the relationship among drivers becomes more harmonious, which benefits the long-term development of small packages shipping industries.

The mathematical model is established as follow:

Indices and Sets

i, j: Index of a customer or the single depot;

N: Set of all customers with the single depot;

A: Set of all arcs;

k: Index of a driver;

K: Set of all drivers;

t: Index of a day;

T: Set of days in the planning horizon.

Parameters

t_{ij}: Travel time of the arc(i, j), $i, j \in N$.

s_i^t: Service time of customer i on day t, $i \in N, t \in T$

r_i^t: Demand quantity of customer i on day t; $i \in N \backslash \{0\}$, $t \in T$.

e_i^t: Equaling one if customer i requires service on day t ($r_i^t > 0$), otherwise zero.

C: Capacity of the vehicle.

L: Maximal workload of each driver per day

Θ: The allowed maximal workloads' difference among drivers.

Decision Variables

$\alpha_{ijk}^t = \{0, 1\}$: Equaling one if driver k traverses arc $(i, j \in A)$ on day $t \in T$, and zero otherwise;

$\beta_{ki}^t = \{0, 1\}$: Equaling one if driver k serves customer i on day $t \in T$, and zero otherwise;

$\delta_i^t \geq 0$: A nondecreasing indicator, showing the sequence to visit each customer on day t (for subtour elimination purpose);

$\omega_k^t \geq 0$: Workload of driver k on day t;

$\lambda_k = \{0, 1\}$: Equaling one if driver k is not idle over the period, and zero otherwise.

MILP Formulation

$$\text{(P1) min} \quad \sum_{t\in T}\sum_{k\in K}\sum_{(i,j)\in A} t_{ij}\alpha_{ijk}^t + \sum_{k\in K}\sum_{i\in N\{0\}}\sum_{t\in T} s_i^t\beta_{ki}^t \tag{1}$$

$$\text{s.t.} \quad \sum_{j\in N}\alpha_{ijk}^t = \beta_{ki}^t \quad \forall k \in K,\ \forall i \in N \setminus \{0\},\ \forall t \in T; \tag{2}$$

$$\sum_{j\in N\setminus\{0\}} \alpha_{0jk}^t \leq 1 \quad \forall k \in K,\ \forall t \in T; \tag{3}$$

$$\sum_{k\in K}\beta_{ki}^t = e_i^t \quad \forall i \in N \setminus \{0\},\ \forall t \in T; \tag{4}$$

$$\sum_{i\in N} r_i^t\beta_{ki}^t \leq C \quad \forall k \in K,\ \forall t \in T; \tag{5}$$

$$\sum_{(i,j)\in A} t_{ij}\alpha_{ijk}^t + \sum_{i\in N\{0\}} s_i^t\beta_{ki}^t \leq L \quad \forall k \in K,\ \forall t \in T \tag{6}$$

$$\sum_{j\in N}\alpha_{ijk}^t - \sum_{j\in N}\alpha_{jik}^t = 0 \quad \forall k \in K,\ \forall i \in N,\ \forall t \in T; \tag{7}$$

$$\sum_{(i,j\in A)} t_{ij}\alpha_{ijk}^t + \sum_{i\in N\{0\}} s_i^t\beta_{ki}^t = \omega_k^t \quad \forall k \in K,\ \forall t \in T; \tag{8}$$

$$\beta_{ki}^t \leq \lambda_k \quad \forall k \in K,\ \forall i \in N \setminus \{0\},\ \forall t \in T \tag{9}$$

$$\sum_{t\in T}\omega_k^t - \sum_{t\in T}\omega_{k'}^t \leq \Theta + M(1-\lambda_k) + M(1-\lambda_{k'}) \quad \forall k, k' \in K; \tag{10}$$

$$\delta_j^t \geq \delta_i^t + 1 - |N|\left(1 - \sum_{r\in R}\alpha_{ijk}^t\right) \quad \forall (i, j) \in A:\ j \neq 0; \tag{11}$$

$$\alpha_{ijk}^t, \beta_{ki}^t = \{0, 1\} \tag{12}$$

$$\delta_i^t, \omega_k^t, \lambda_k \geq 0. \tag{13}$$

Objective (1) minimizes the total workload of all the drivers. The workload of drivers includes two parts: one is the traveled time, and the other is the service time. Constraints (2) ensure that customers are visited at most once on day t. Constraints (3) state that the drivers with the workload on day t should start from the deport '0' to visit customers, or this driver does not have workload on that day. Constraints (4) ensure that if a customer has demand on day t, then this customer must be visited by a driver on that day. Constraints (5) are the capacity constraints, which guarantee that the served total load requirement of a driver on day t should not exceed a vehicle's load capacity. Constraints (6) are the travel time constraints, which guarantee that the total workload of a driver on one day is no more than the maximal workload. Constraints (7) state that each customer has only one predecessor and one successor. Constraints (8) state the definition of the workload of drivers, which contains the traveled time and service time. Constraints (9) guarantee that if a driver has worked on one day, then this driver is not idle over the planning period. Constraints (10) guarantee that any two drivers' workload should not exceed maximal workload difference. Constraints (11) serve to eliminate subtours in the individual daily routes. Constraints (12)-(13) define the decision variables.

4. Solution Methodology

The local branching based method plays a very important role in improving the incumbent solution as early as possible during the computation when solving difficult MIP problems. It adopts a two-level branching strategy whose high-level strategic branching defines solution neighborhoods and low-level tactical branching explores them. The core idea is to find an initial solution and use the CPLEX solver as a 'lower-level' black-box tool for exploring solution subspaces, which are then controlled at a 'higher-level' by an external branching framework. The difference from other solution methods is that the neighborhoods are formulated by introducing some linear inequalities, which are called 'local branching cuts'. In our study, the local branching based method is to branch the binary variable β_{ki}^t within its solution space, because the variable β_{ki}^t is the critical decision variable in the model, as it determines the remaining variables such as α_{ijk}^t. The basic

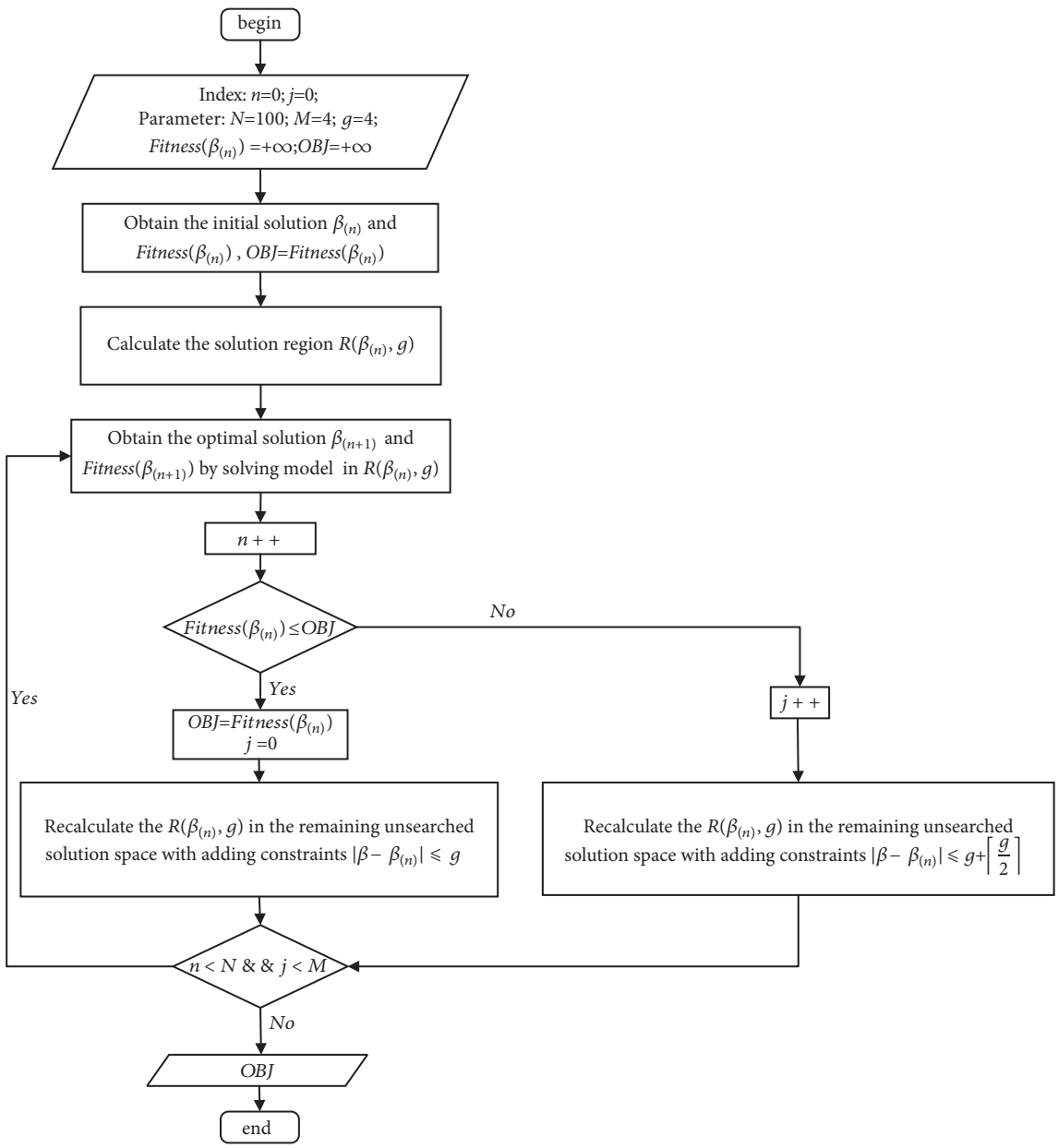

Figure 3: The basic procedure of local branching.

procedure of this local branching based method is shown in Figure 3.

In Figure 3, several important parameters should be determined firstly; thereinto, g is the neighborhood-size parameter, and it should be chosen as small to reduce the computing time, but still large enough to ensure that better solutions can be found. N is the maximal number of iterations, and M is the allowable consecutive number of unimproved solutions found in the iterating process; both are the stopping conditions of the whole procedure; once one of them is exceeded, the procedure stops. OBJ is the objective value. In this procedure, $\boldsymbol{\beta}_{[n]}$ denotes the optimal solution that can be found in the nth iteration, and the initial solution is denoted by $\boldsymbol{\beta}_{[n]}$ where $n = 0$. The fitness value in the nth iteration is denoted by $Fintness(\boldsymbol{\beta}_{[n]})$.The initial solution is obtained by initializing the binary variables β_{ki}^{t} $(\forall k \in K, i \in N, t \in T)$ when solving the model proposed in Section 3; then a solution region $R(\boldsymbol{\beta}_{[0]}, g)$ is calculated by a constraint $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \leq g$. Here $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}|$ reflects the radius of $\boldsymbol{\beta}_{[0]}$'s neighborhood in the solution space, and it is calculated as follows: $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| = \sum_{k\in K}\sum_{i\in N}\sum_{t\in T}|\beta_{ki}^{t} - \beta_{ki}^{t\,[0]}|$. After that, the improved solution $\boldsymbol{\beta}_{[1]}$ will be obtained by solving model in the $R(\boldsymbol{\beta}_{[0]}, g)$. In the next iteration, as the searched space (i.e., $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \leq g$) will no longer be searched, the solution region $R(\boldsymbol{\beta}_{[1]}, g)$ will be recalculated by constraints $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \geq g + 1$ and $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[1]}| \leq g$. And the optimal solution $\boldsymbol{\beta}_{[2]}$ obtained by solving the same model in a new solution

The procedure of handling strategy to two cases:
if $elapsed\_time(n) \geq time\_limit$ **then** //$elapsed\_time(n)$ is the running time of solving model in the solution region $R(\boldsymbol{\beta}_{[n]}, g)$.
  if $Fitness(\boldsymbol{\beta}_{[n]}) < OBJ$ **then**
    $OBJ \longleftarrow Fitness(\boldsymbol{\beta}_{[n]})$;
    Recalculate the $R(\boldsymbol{\beta}_{[n]}, g)$ by the constraints $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \geq g + 1, \cdots, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n-2]}| \geq g + 1, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n]}| \leq g$;
  else
    Recalculate the $R(\boldsymbol{\beta}_{[n]}, g)$ by the constraints $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \geq g + 1, \cdots, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n-2]}| \geq g + 1, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n-1]}| \leq \lfloor g/\boldsymbol{\alpha} \rfloor$ //α is an integer.
  end if
end if

Pseudocode 1

region $R(\boldsymbol{\beta}_{[1]}, g)$ will replace the $\boldsymbol{\beta}_{[1]}$ if $Fintness(\boldsymbol{\beta}_{[2]})$ is better than the OBJ. Repeating the updating procedure until the stop condition is reached, then we will obtain the final objective value.

The basic procedure of local branching method has two points to be noted: One is related to the solution region. As the searched space will no longer be searched again, the solution region will be recalculated according to constraints $|\boldsymbol{\beta}-\boldsymbol{\beta}_{[0]}| \geq g+1, \cdots, |\boldsymbol{\beta}-\boldsymbol{\beta}_{[n-1]}| \geq g+1, |\boldsymbol{\beta}-\boldsymbol{\beta}_{[n]}| \leq g$ in each iteration. The other is the situation that the solution found is worse than the incumbent solution in an iteration; once the situation occurs, a diversification consisting in enlarging the current solution region can be applied, e.g., changing the constraint $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[n]}| \leq g$ into $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[n]}| \leq g + \lceil g/2 \rceil$.

Imposing a time limit on the subprocedure of solving model in the solution region $R(\boldsymbol{\beta}_{[n]}, g)$ will enhance heuristic performance of the local branching method. In case the time limit is exceeded, there will be two cases.

(1) The incumbent solution has been improved when the time limit is reached. In this situation, the handling strategy is solving the model in the solution region calculated by $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[0]}| \geq g + 1, \cdots, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n-2]}| \geq g + 1, |\boldsymbol{\beta} - \boldsymbol{\beta}_{[n]}| \leq g$ in the nth iteration, and the solution region in the next iteration will be within the remaining searchable space with a constraint $|\boldsymbol{\beta} - \boldsymbol{\beta}_{[n+1]}| \leq g$.

(2) The time limit is reached with unimproved solution. Once it happened, we can reduce the size of the solution region to speed up its exploration.

The handling procedure of the above two cases is illustrated by Pseudocode 1.

The basic procedure and enhancing strategies are the whole content of local branching method. Though not complex, the method proved quite effective when solving difficult MIPs.

5. Computational Experiments

This section presents a series of experiments to validate the effectiveness of the MILP model and the local branching based method. In Section 5.1, we solve a set of small problems and compare the results obtained by local branching based method with the objective values obtained by CPLEX. And we solve a number of small and medium scale instances by local branching based method in Section 5.2 to conduct a sensitivity analysis for exploring the effect of workload differential on the total workload of drivers. To validate the efficiency of the proposed MILP model and solution method, we perform numerical experiments on a PC (Intel Xeon Gold 6154 Processor, 3.00G Hz; Memory, 512G). The algorithm is implemented by C# using the CPLEX of version 12.5.

5.1. Performance Comparison of CPLEX and Local Branching Based Method. The small scale data consists of five problems with 10 customer locations and five problems with 12 customer locations. The probability that a customer requires service on a given day was set to 70%, and the planning period is T=3. The data about the locations of customers and depot and the number of customers' demands is randomly generated. In addition, the allowed working time for each driver per day is L=35, and the vehicle's capacity is C=15 for all problems. The maximal workload differential among drivers is set as Θ=10, and the available number of divers is K=2 in 10 customers and K=3 in 12 customers to guarantee that all the instances can be solved. We solve these instances by CPLEX and local branching based method, and the results are shown in Table 1.

As shown in Table 1, column '$\boldsymbol{GAP}_L$' records the gaps between the solutions obtained by local branching based method and the solutions obtained by CPLEX's MILP solver. Note that, if the value of '$\boldsymbol{GAP}_L$' is negative, it implies the local branching based method is better than the CPLEX's solution. From Table 1, we can see that CPLEX can find feasible solutions of all instances within two hours. In comparison, the local branching based method can mostly obtain better solutions in a quite short time period. Moreover, with the instances' scale increasing, the average improvement ratio of local branching based method is from 7.33% to 27.63%, and the computational time is slightly increased. So, we can conclude that the performance of local branching based method is much better than the CPLEX, especially on the larger scale. In the next section, we conduct sensitive analysis by using local branching based method.

Table 1: The performance comparison of CPLEX and local branching based method.

Instances	CPLEX		Local Branching		GAP_L	T_L/T_C
ID	Z_C	T_C	Z_L	T_L		
10_1	138.0	7200	138.0	615	0.00%	0.09
10_2	124.0	7200	118.7	604	-4.27%	0.08
10_3	151.7	7200	148.3	605	-2.24%	0.08
10_4	158.5	7200	148.6	607	-6.25%	0.08
10_5	160.8	7200	122.3	603	-23.90%	0.08
Average					-7.33%	0.08
12_1	171.0	7200	161.3	915	-5.67%	0.13
12_2	165.9	7200	110.9	605	-33.20%	0.08
12_3	187.7	7200	129.5	608	-31.01%	0.08
12_4	225.9	7200	165.0	606	-26.96%	0.08
12_5	223.9	7200	131.4	606	-41.31%	0.08
Average					-27.63%	0.09

Notes: (1) The ID '10-1' means there are 10 customers in this instance, and '1' is the index of the instance. (2) Objective value and CPU time for CPLEX are denoted by Z_C and T_C. Objective value and CPU time for local ranching based method are denoted by Z_L and T_L, and $GAP_L = (Z_L - Z_C) / Z_C$.

Table 2: sensitivity analysis on workload differential.

ID	K	No consideration of θ			Consideration of θ			*gap*
		Z_L	T_L	$(1/5)\omega$	θ	Z_L'	T_L'	
10-1	2	138.0	439	4.60	3	138.0	1930	0.00%
10-2	2	118.6	1960	3.95	3	118.8	1949	0.17%
10-3	2	148.2	1938	4.94	3	148.3	1938	0.07%
10-4	2	148.6	1929	4.95	3	151.3	1946	1.78%
Average			1567				1941	0.51%
15-1	2	809.4	2409	26.98	10	811.1	2714	0.21%
15-2	2	963.8	2470	32.13	12	966.4	2430	0.27%
15-3	3	1188.3	2471	26.41	10	1296.7	3405	8.36%
15-4	2	751.5	1809	25.05	10	751.6	2411	0.01%
Average			2290				2740	2.21%
20-1	2	861.9	1907	28.73	20	862.4	2510	0.06%
20-2	3	1121.4	2517	24.92	20	1238.6	2210	9.46%
20-3	3	1322.1	2235	29.38	20	1328.0	4645	0.44%
20-4	2	876.9	2444	30.20	20	879.6	3362	0.31%
Average			2276				3182	2.57%

Notes: (1) 'K' is the number of drivers; 'ω' denotes the average workload of each driver on a day, which is obtained by the function $\omega = Z_L/(T \times K)$. (2) θ denotes the value of maximal workload differential among drivers which is the input parameter to solve the problem. Here, $\theta < (1/5)\omega$. (3) '*gap*' is calculated by the function *gap*= $(Z_L' - Z_L)/Z_L'$; Z_L and T_L are the objective value and CPU time of local branching which do not consider small workload differential, respectively; and Z_L' and T_L' are the objective value and CPU time of local branching which consider small workload differential, respectively.

5.2. Sensitivity Analysis. In order to explore the effect of small workload differential among drivers on the total workload, we conduct a sensitivity analysis on this section. Firstly, we generated three group instances which range from 10 customers to 20 customers. In each group, there are four instances. The data about locations of customers and depot and the number of customers' demands are randomly generated as well. The planning period in all instances is T=3. In addition, the allowed working time for each driver per day is L=35, the vehicle's capacity is C=15 for small scale instances (10 customers), and C=160, L=200 in medium scale instances (15-20 customers). Secondly, we do not consider the workload differential among drivers, and we solve these instances to obtain the minimal total workload. After obtaining the minimal total workload, in order to explore the effect of small workload differential among drivers on the total workload, we set the maximal workload differential among drivers to be no more than the one-fifth of the average workload of a driver on a day, solve these instances, and obtain the updated objectives. The results are shown in Table 2.

From Table 2 we can see that the objective value of considering small workload differential among drivers is larger than the objective value of no limit to workload differential among drivers, which means that achieving workload balance will increase the total workload (cost). With the instances' scale increasing, the gap between no consideration

and consideration workload differential becomes larger, the average gap is from 0.51% to 2.57%, and the computational time is longer as well. What should be mentioned is that the gap on the small and medium scale is in an accepted range, so it is advisable for managers to achieve a balanced workload for drivers with small increased cost.

6. Conclusion

This study examines an operations management problem of shipping industry which aims to balance the workload among drivers. For solving this problem, a mixed-integer linear programming model is proposed. Different from the general vehicle routing problem, this model adds a new constraint to limit the workload differential among drivers. Moreover, we use a local branching based method to solve this problem on different scales, which can obtain better and faster solutions for large instances of the problem. To validate the efficiency of the proposed model and the local branching based method, numerical experiments are conducted. The results indicate that local branching based method can accelerate the solving time and obtain better solutions compared with CPLEX. Moreover, from the result of sensitivity analysis, we can discover that considering a balanced workload among drivers will lead to an increase in cost, but the increased cost is in an accepted range. For managers of the delivery industry, it is advisable to balance workload among drivers with fewer increased cost, so as to improve the service quality and reliability.

The problem we studied was to minimize the total workload of all drivers with considering small workload differential among drivers, which provides a new perspective to improve service quality and reliability. At present, we used local branching based method to solve this problem on a small and medium scale. In the future, we aim to design a new heuristic algorithm to solve this problem on a larger scale in a reasonable time. Moreover, the essential goal is improving service quality and reliability, so we will consider more factors like consistent service with different implementation in our research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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