

Received April 14, 2020, accepted April 26, 2020, date of publication April 30, 2020, date of current version May 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2991411

A Hyper-Heuristic Algorithm for Time-Dependent Green Location Routing Problem With Time Windows

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This work was supported by the Zhejiang Provincial Natural Science Foundation of China under Grant LY18F030010.

ABSTRACT The Location Routing Problem (LRP), a branch of logistics management, has been addressed in many research papers. However, there are few papers on time-dependent LRP. And only a few of them take fuel consumption into consideration. To reduce the environmental pollution from vehicle emissions and the cost pressure on logistics, a novel model named the time-dependent green location routing problem with time windows (TDGLRP) is developed. Its objective is to minimize costs including opened depot costs, enabled vehicle costs and fuel consumption costs. In TDGLRP the speed and travel times are time-dependent function. A hyper-heuristic algorithm (HH) that consists of two levels, high-level heuristics (HLHs) and low-level heuristics (LLHs), is proposed to solve the TDGLRP. The Tabu Search (TS) algorithm is taken as the high-level selection mechanism, and the Greedy algorithm is taken as the acceptance mechanism. With reference to the Solomon benchmarks, we design a series of TDGLRP instances with 100 client nodes, and analyze the impact of client distribution characteristics on the path. Based on the TDGLRP model and HH, the end of the article gives the solution results of a large-scale instances with 1000 nodes.

INDEX TERMS Time-dependent, location-routing problem, fuel consumption, emission, hyper-heuristic.

I. INTRODUCTION

Urban logistics play an important role in the economy, society, environment, and citizens [1]. The Location Routing Problem (LRP) is a branch of logistics management [2] and conducts joint decision-making with regard to the locations of arbitrary types of facilities and the routing of vehicles [3]. As one of the most important optimization problems in logistics system planning [4], the LRP can be traced back to 1961 [5]. However, the importance of coordinating the location and vehicle route was not truly recognized until the 1970s [6], [7]. With further research, a number of LRP variants with different constraints have been developed, such as the LRP with time windows [8], the LRP with simultaneous pickup and delivery [5], [9], and the bi-objective LRP [10]. For more information on the variants of the LRP, the reader can refer to the following two surveys [11], [12]. In the last decade, consumers, businesses and governments have increased their attention to the environment [13].

The associate editor coordinating the review of this manuscript and approving it for publication was Zhiwu Li¹.

City logistics, as a primary source of carbon emissions, should be formulated to initiate carbon emission reductions during related activities [14], [15]. As an essential tool in the supply chain, the LRP should consider fuel consumption and emission reductions. The LRP that considers environmental issues can be called the Green LRP (GLRP) [16].

In traditional LRP, that the travel time between two nodes are constant, and the Euclidean distances between nodes are often used as the travel times. However, in real road network, the travel speed and travel time are time dependent function. The time-dependent LRP problem is more instructive to the logistics.

The literature relating to time-dependent and green LRP are not very common. We searched the literature on GLRP in recent years and classified them by year.

A. 2016

In this year, we found three papers on the GLRP. Koç *et al.* [1] investigated the combined impact of the depot location, fleet composition and routing decisions on vehicle emissions in city logistics. Its objective was to minimize the total costs

including the depot costs, vehicle and routing costs and emissions costs. The feature of this paper is that the clients are located in nested zones with different speed limits. In addition, a new powerful adaptive large neighborhood search meta-heuristic was developed. Tang *et al.* [17] established a bi-objective model of costs and carbon emissions from the perspective of a sustainable supply chain network. In this paper, a multi-objective particle swarm optimization algorithm was used. A computational experiment and sensitivity analysis were conducted using data from the China National Petroleum Corporation. The results indicated that the research can be applied to actual supply chain operations. Based on the assumptions of time windows and split-delivery, Qazvini *et al.* [18] presented a mixed integer linear model for the so-called green routing problem. The model had been successfully applied to a light auto parts distribution chain.

B. 2017

Rabbani *et al.* [19] introduced a new variant of the Multi-objective Green Location Routing Problem (MOGLRP) to minimize the total traveled distances and the total costs including the vehicle fixed costs and variable travel costs and the CO₂ emissions. The fleet distribution is heterogeneous. Similar to Rabbani, Wang and Li [20] also considered the GLRP problem with a heterogeneous fleet, and considered the constraints of simultaneous pickup-delivery and time windows. The paper introduced the concept of temporal-spatial distance, which made the quality of the initial solution higher. Toro *et al.* [21] proposed a multi-objective GLRP model to minimize the operational costs and minimize the environmental effects. The model shows that the fuel consumption is related to the vehicle weight, speed, road slope and wind resistance. To simplify the calculation, the average speed and average slope were used in this paper. Zhang *et al.* [22] simplified fuel consumption as a function of load and distance.

C. 2018

In this year, many researches on GLRP mainly focused on its application and update solution algorithm. Chen *et al.* [15] and Wang *et al.* [23] successfully applied the GLRP model to cold chain logistics. Faraji and Nadjafi [24], Longlong *et al.* [25], Leng *et al.* [26], Zhao *et al.* [27] and Qian *et al.* [28] used the new hyper-heuristic algorithm to solve the GLRP. They proved the efficiency of the hyper-heuristic algorithm at solving the GLRP problems.

D. 2019-2020

From 2019 to the present, multi-objective GLRP problems remain the focus of research [14], [29]. At the same time, the influence of vehicle speed on fuel consumption and emissions has received increasing attention. For example, Leng *et al.* [4] and Koç *et al.* [1] divided the logistics distributed field into three speed zones and the speed of each zone was different.

The papers mentioned above have different optimization strategies for the fuel consumption and emissions. The optimization objectives of some papers are to minimize the

costs, which includes the fuel consumption costs or emissions [1], [22]. One paper takes the fuel consumption as a constraint [18]. The other papers take the fuel consumption or emissions as one of several optimization objectives. Another difference between these papers is the method of calculating fuel consumption. As we all know, fuel consumption is affected by many factors, such as the vehicle's own parameters, weather factors, vehicle speed factors and so on [30], [31]. Among these factors, speed is the most critical one [14]. However, one part of the literature above did not consider the effect of vehicle speed and the other part did not consider the time variability of speed. In the actual road network, the vehicle speed is variable and dynamic because of the traffic flow, weather, accidents and other factors. It will lead to deviations of up to 20% in emissions for gasoline vehicles on an average day and up to 40% in congested traffic if a constant vehicle speed is used to calculate fuel consumption [32]. Therefore, this paper adopts a time-dependent GLRP model. The main work and contributions of this paper can be stated as follows.

E. PROBLEM AND MODEL

A mixed-integer programming model named TDGLRP is developed by using a comprehensive fuel consumption function. The objective is to minimize the total costs including the opened depots cost, fixed vehicle costs and fuel consumption costs. Compared to the traditional LRP, the delivery network is dynamic and the speed is a function of time. The schematic diagram of the TDGLRP problem is shown in FIGURE 1.

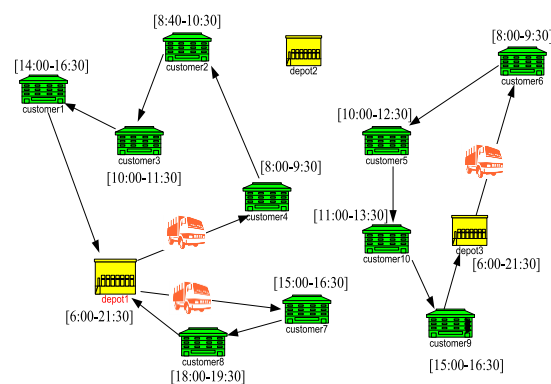


FIGURE 1. The diagram of the TDGLRP.

F. EFFICIENT OPTIMIZATION ALGORITHM

To solve the TDGLRP, a hyper-heuristic algorithm (HH) is proposed. There are two levels in the HH framework: high-level heuristics (HLHs) and low-level heuristics (LLHs). The Tabu Search (TS) is taken as the high-level selection mechanism, and the Greedy algorithm is taken as the acceptance mechanism. Moreover, this paper applied an insertion method based on the travel time (IMTT) to generate the initial population, which is critical to the quality of the final solution.

The remainder of this paper is organized as follows. Section 2 focuses on the modeling. Section 3 introduces the

IMTT and HH. Section 4 mainly introduces the results and analysis. The last section is a summary.

II. DESCRIPTION AND MATHEMATICAL MODEL

In this section, the fuel consumption model and the TDGLRP model will be introduced.

A. PROBLEM DESCRIPTION

The TDGLRP studied here is defined on an asymmetric directed graph $G = (V, E)$, where V is a set of nodes and E is a set of edges ($E = \{(i, j) : i, j \in V, i \neq j\} \cup \{(i, j) : i, j \in D\}$). In addition, V consists of a set D ($D = \{1, 2, \dots, M\}$) of potential depots and a set C ($C = \{1, 2, \dots, N\}$) of clients. Each client $i \in C$ has known demands q_i , service time ST_i , geographical location (x_i, y_i) and hard time window $[a_i, e_i]$. A hard time window means that if the vehicle arrives at client i earlier than a_i , it must wait until a_i to start service. The capacity P_j , the rent cost FD_j and the coordinates (x_j, y_j) of the candidate depot j ($j \in C$) are known. Each vehicle h in the homogeneous fleet has the same capacity Q_h and rent cost FV_h . The symbol d_{ij} represents the distance between the two nodes i and j ($i \neq j \in V$). The travel time depends on the speed, which changes according to the departure time and the arc being traversed. The vehicle traversing different arcs has different travel speeds $V(t)$, $t \in S = \{t_0, t_0 + \Delta, \dots, t_0 + (M-1)\Delta\}$, where t_0 is the earliest time from any node in the network, Δ is the time interval, M is the time zone.

B. TRAVEL TIME CALCULATION

Based on the time windows and the speed time-dependent function, we calculate the travel time via the following approach.

The total server time window is divided into M equal time zones: $S = \{t_0, t_0 + \Delta, \dots, t_0 + (M-1)\Delta\} = \{T_1, T_2, \dots, T_M\}$. And assuming one vehicle is driving from A to B, it may reach point B in different time zone (see **FIGURE 2**). Now finding the travel time from A to B. Assuming the vehicle departs from A at time t_0 .

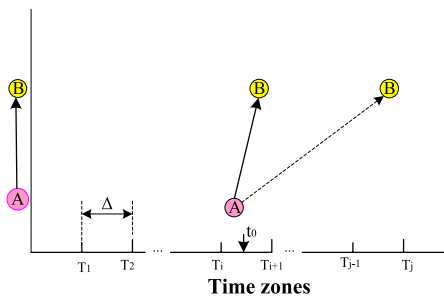


FIGURE 2. Temporal-spatial figure from A to B.

There are two possibilities: one is that the vehicle arrives at B before T_{i+1} (see the solid line in **FIGURE 2**), and the other is that it arrives at B after T_{i+1} (see the dotted lines). For the second case, assuming that the vehicle reaches B in $[T_{j-1}, T_j]$. The distance between A and B is d_{ij} , and vehicle

speed at time t is expressed as $V(t)$, then the travel time TT_{AB} from A to B is calculated as follow formula:

$$TT_{AB} = \begin{cases} \beta, \beta + t_0 \leq T_{i+1} \\ T_{i+1} - t_0 + \lambda \cdot \delta \\ (d_{AB} - (T_{i+1} - t_0) \times V(t_0) - \sum_{n=i+1}^{j-2} \delta \times V(n)) \\ + \frac{V(j-1)}{V(j-1)}, \dots \\ \beta + t_0 > T_{i+1}, (j-2) > (i+1) \\ T_{i+1} - t_0 + \frac{(d_{AB} - (T_{i+1} - t_0) \times V(t_0))}{V(j-1)}, \\ \beta + t_0 > T_{i+1}, (j-2) \leq (i+1) \end{cases}$$

where $\beta = d_{AB}/V(t)$.

C. FUEL CONSUMPTION MODEL

We estimate the fuel consumption and emissions that is based on the Comprehensive Modal Emission Model (CMEM) [33], which has been widely used in LRP. The CMEM can accurately predict the fuel consumption and emissions [1], [34]. if a vehicle h traveling from node i to node j , the fuel consumption over this segment can be obtained by (1) using the CMEM model:

$$\begin{cases} P_{tract} = ((W + K_{ijh}) \cdot a + (W + K_{ijh}) \cdot g \cdot \sin \theta + \dots \\ 0.5 \cdot C_a \cdot F_a \cdot \rho \cdot v_{ijh}^2 + (W + K_{ijh}) \cdot g \cdot C_r \cdot \cos \theta) \cdot \frac{v_{ijh}}{1000} \\ P = \frac{P_{tract}}{n_{ef}} + P_{acc} \\ FR = \xi \cdot (E_f \cdot E_s \cdot E_d + \frac{P}{\eta}) / k \\ F_{ijh} = FR \cdot \frac{d_{ij}}{v_{ijh}} \end{cases} \quad (1)$$

where P_{tract} (kW) is the total traction power requirement; K_{ijh} (kg) is the load of the vehicle h moving from node i to node j ; P (kW) is the second-by-second engine power output; P_{acc} is the engine power demand associated with the running losses of the engine (here, $P_{acc} = 0$); FR (g/s) is the fuel consumption rate; v_{ijh} (m/s) is the speed of the vehicle from node i to node j ; d_{ij} (m) is the distance between nodes i and j ; F_{ijh} (g) is the fuel consumption of the vehicle from node i to node j ; and θ is the road angle, and here its value of each road is equal to 0 [2], [35]. TABLE 1(a) and (b) gives the parameters used in the above model for estimating the fuel consumption [36], [37].

D. MATHEMATICAL MODEL

Before providing the proposed model, several assumptions should be made: (1) each client must be served only once and must start being served within the time window; (2) each vehicle must return to the original depot, (3) The capacity of each vehicle and of each depot cannot be exceeded. The other

TABLE 1. Vehicle parameters.

(a)		
Common parameters for all vehicle types		
Symbol	Description	Value
ζ	Fuel-to-air mass ratio	1
g	Gravitational constant (kg/m ²)	9.81
ρ	Air density (kg/m ³)	1.2041
C_r	Coefficient of the rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
k	Heating value of typical diesel fuel (kJ/g)	43.2
n_{df}	Vehicle drivetrain efficiency	0.45

(b)		
Vehicle specific parameters		
Symbol	Description	Value
W	Curb weight (kg)	3500
E_f	Engine friction actor (kJ/rev/L)	0.25
E_s	Engine speed (rev/s)	38.34
E_d	Engine displacement (L)	4.5
C_a	Coefficient of aerodynamic drag	0.6
F_a	Frontal surface area (m ²)	7.0

TABLE 2. Parameters and variables.

Symbol	Description
K_{ijh}	Load of vehicle h leaving i and traveling to j
ST_j	Service time of client j
AT_{jh}	The time when vehicle h arrives at node j
TT_{ij}	Travel time between nodes i and j
y_r	1 if depot r is open, and 0 otherwise
z_{im}	1 if client i is served by depot m , and 0 otherwise
x_{ijh}	1 if the vehicle h travels from i to j , and 0 otherwise

index sets, parameters, and decision variables in the model are listed in TABLE 2.

The proposed model seeks to minimize the total costs including the depot costs, vehicle costs and FC costs, and can be represented as follows.

Objective function:

$$f = \min(f_1 + f_2) \quad (2)$$

where:

$$f_1 = \sum_{r \in D} FD_r y_r + FV \times \sum_{i \in D} \sum_{j \in C} \sum_{h \in H} \sum_{m=1}^M x_{ijh}^m \quad (3)$$

$$f_2 = \sum_{i \in G} \sum_{j \in G} \sum_{h \in H} \sum_{m=1}^M x_{ijh}^m F_{ijh}^m \quad (4)$$

Distance function:

$$f_3 = \sum_{i \in G} \sum_{j \in G} \sum_{h \in H} \sum_{m=1}^M x_{ijh}^m d_{ij}^m \quad (5)$$

Travel time function:

$$f_4 = \min \left(\sum_{i \in G} \sum_{j \in G} \sum_{h \in H} \sum_{m=1}^M (x_{ijh}^m TT_{ij}^{m'}) + \max(e_i - AT_i, 0) + ST_i \right) \quad (6)$$

The following constraints must be satisfied:

$$\sum_{i \in V} \sum_{h \in H} \sum_{m=1}^{TM} x_{ijh}^m = 1, \quad \forall j \in C \quad (7)$$

$$\sum_{h \in H} \sum_{i \in V} \sum_{m=1}^{TM} x_{ijh}^m = \sum_{h \in H} \sum_{i \in V} \sum_{m=1}^{TM} x_{jih}^m, \quad \forall j \in C \quad (8)$$

$$\sum_{j \in D} z_{ij} = 1, \quad \forall i \in C \quad (9)$$

$$\sum_{m=1}^{TM} x_{ijh}^m + \sum_{k \in H, k \neq h} \sum_{r \in V, r \neq j} \sum_{m=1}^{TM} x_{jrk}^m \leq 1, \quad i \in V, j \in V, i \neq j, h \in H \quad (10)$$

$$\sum_{h \in H} \sum_{m=1}^{TM} x_{ijh}^m \leq z_{ij}, \quad \forall i \in C, j \in D \quad (11)$$

$$\sum_{h \in H} \sum_{m=1}^{TM} x_{jih}^m \leq z_{ij}, \quad \forall i \in C, j \in D \quad (12)$$

$$\sum_{h \in H} \sum_{m=1}^{TM} x_{ijh}^m + z_{ik} + \sum_{m \in D, m \neq k} z_{jm} \leq 2, \quad \forall i, j \in C, k \in D, i \neq j \quad (13)$$

$$\sum_{i \in D} \sum_{j \in C} K_{ijh} = \sum_{i \in C} \sum_{j \in V} \sum_{m=1}^{TM} x_{ijh}^m q_i, \quad \forall h \in H \quad (14)$$

$$\sum_{i \in C} \sum_{j \in D} K_{ijh} = 0, \quad \forall h \in H \quad (15)$$

$$\sum_{i \in C} q_i z_{ik} \leq P_k y_k, \quad \forall k \in D \quad (16)$$

$$\sum_{i \in V} \sum_{h \in H} (K_{ijh} - q_j) x_{ijh} = \sum_{i \in V} \sum_{h \in H} \sum_{m=1}^{TM} x_{ijh}^m K_{jih}, \quad \forall j \in C \quad (17)$$

$$K_{ijh} \leq \sum_{m=1}^{TM} x_{ijh}^m Q_h, \quad \forall i, j \in V, i \neq j, h \in H \quad (18)$$

$$K_{ijh} \geq \sum_{m=1}^{TM} x_{ijh}^m q_j, \quad \forall i \in V, j \in C, h \in H \quad (19)$$

$$AT_{jh} = x_{ijh} \cdot (\max\{e_i, AT_{ih}\} + ST_i + TT_{ijh}), \quad \forall i, j \in V, h \in H \quad (20)$$

$$0 \leq AT_{jh} \leq l_j, \quad \forall j \in C, h \in H, x_{ijh}^m \in \{0, 1\}, \quad \forall i, j \in V, h \in H, m \in TM \quad (21)$$

$$y_j \in \{0, 1\}, \quad \forall j \in D \quad (22)$$

$$z_{ij} \in \{0, 1\}, \quad \forall i \in C, \forall j \in D \quad (23)$$

The description and explanation are as follows. Equation (2) is the optimize objective of the TDGLRP;(3) is the costs of vehicles and depots;(4) is the fuel consumption function;(5) is total distances function;(6) is the total travel time function; Constraints (7) and (8) make sure that each client is served exactly once. Constraints (9) and (10) impose that each client is assigned to only one depot and one vehicle. Constraints (11)-(13) forbid unfeasible routes that do not return to the departure depot. Constraints (14) and (15) make sure that the demand of each client is met. Constraint (16) guarantees that the load of each selected depot must be less than its capacity. Constraint (17) is the dynamic equilibrium of the load of each vehicle after visiting client j . Constraints (18) and (19) guarantee that the vehicle capacity is not exceeded. Constraints (20-21) are the time window constraints. Finally, the last three constraints are decision variables.

III. HYPEY HEURISTIC ALGORITHM

This section describes the hyper-heuristic algorithm that is used to solved the TDGLRP model.

The hyper-heuristic(HH) algorithm system was defined as a “heuristic selection heuristic” algorithm [38]–[40]. The HHs algorithm have been widely used in operational optimization problems such as the Vehicle Routing Problem (VRP) [41], VRP with time windows (VRPTW) [42], LRP [43] and low carbon LRP [28]. HH is divided into two levels: low-level heuristics (LLHs) in the problem domain and high-level heuristics (HLHs) in the control domain. The LLHs provide a series of low-level heuristics and problem definition, objective function and other information. The HLHs automatically produce an adequate combination of the provided HLHs components to effectively solve the given problems [44]. The framework of hyper heuristic algorithm is shown in Figure 3.

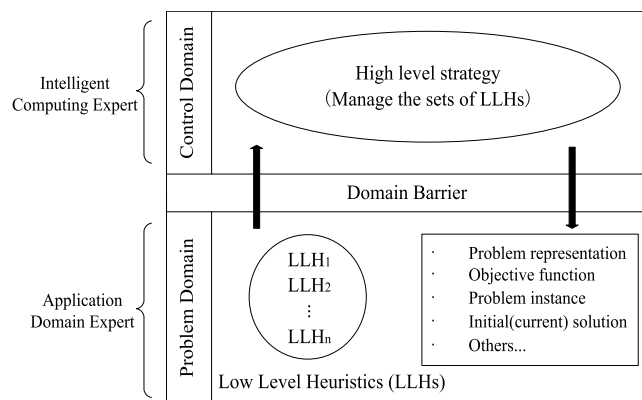


FIGURE 3. The framework of the HH [28].

It is very important to design efficient selection strategies and acceptance criteria in the HH. There are many selection strategies (SA) include the simple random (SR) sampling, choice function (CF), genetic algorithm (GA) [45], [46], Tabu Search (TS) [47], [48], and quantum evolutionary algorithm (QEA) [25] strategies. SA falls into two categories: deterministic acceptance, which accepts the resultant solution based on

the fitness or special rules; and non-deterministic acceptance, which accepts the resultant solution based on a threshold or probability [49].

A. LLH OPERATORS

LLHs can be viewed as a “black box”, which are used to perturb the incumbent solution to guide the search by either intensifying or diversifying the search region [2]. In this paper, the LLHs are divided into three parts according to the object: inside one route pools, between two routes pools, and the depot pools. All the operators in the three pools are shown in TABLE 3.

TABLE 3. LLH operators.

pools	Operators	Operating process
Inside one route	K-opt	K sides exchange
	Or-opt	Move the subroute to a new location
	reverse	Reverse one subroute
Between two routes	move	Move one node to a new location
	exchange	Exchange two nodes belonging to different routes
	insert	Insert one node into another route
	Subroute move	Insert one subroute into another route
	Subroute exchange	Exchange two subroutes belonging to different routes
Depot	Shift	Replace an open depot with an unopened depot
	interchange	Interchange the routes of two different depots

B. HIGH-LEVEL HEURISTIC (HLH)

The Tabu Search (TS) is a basis for the development of HH, which guides the next search direction by establishing a tabu list that records the optimization process. Its advantage is that it can avoid falling into the local optimal solution. In this paper, the TS is adopted as the high-level strategy. The search process is as follows [28].

- Each LLH operator k has an initial score $r_k \in [r_{min}, r_{max}]$.
- Select an operator with the highest score in the non-tabu list.
- Update r_k via reinforcement learning method. If the operator k improves the current solution, the operator adds the value $r_k = r_k + b$ ($b > 0$); otherwise, the operator subtracts the value $r_k = r_k - b$. When operator k cannot improve the current solution, it will be put into the tabu list with a fixed length L . In addition, another operator in the tabu list will be removed according to the principle of the “first in, first out” mechanism.

C. ACCEPTANCE CRITERION DESIGN

The acceptance criterion (AC), which is used to determine whether the child solution cf replaces the parent solution pf , directly affects the convergence speed and optimization accuracy of the HH. The HH proposed in this paper adopts a Greedy Algorithm acceptance mechanism. It accepts all the

improved solutions and accepts the non-improved solutions with a certain probability pp , and it can be calculated using equation (25).

$$pp = e^{-(\Delta f/Q)} \quad (24)$$

where $\Delta f = 100 \times (cf - pf)/pf$. Q is the counter used to calculate the number of times the LLH operator continuously fails to improve the pf . As Q increases, the probability of replacing pf with cf is greater. If the selected operator improves the pf , reset Q to 0.

The flow of the HH algorithm is as follows.

The flow of the HH algorithm

```

1: //Initialization
2: Set the parameters
3: Initialize Solution(Pop)
4: CurrentSolution = Pop(r)
5: BestSolution = CurrentSolution
6: Fitness(BestSolution) = Fitness(CurrentSolution)
7: //Main loop
8: while t < ITERdo
9: //High-level Selection Strategy
10: operator = Select( $\xi$ )
11: //low-level heuristics
12: [ChildSolution] = Implement(CurrentSolution, operator)
13: //High-level Acceptance Criterion
14: if Fitness(ChildSolution) < Fitness(CurrentSolution)
then
15: CurrentSolution = ChildSolution
16: else
17: CurrentSolution = Accept or Not (ChildSolution, CurrentSolution)
18: end if
19: //Save the global best solution
20: if Fitness(BestSolution) > Fitness(ChildSolution)
then
21: BestSolution = ChildSolution
22: end if
23: Update related data
23: end while

```

IV. EXPERIMENT AND ANALYSIS

A. BENCHMARKS

In this section, we will expand the Solomon [50] benchmarks to obtain the TDGLRP experimental data. In the Solomon benchmarks, there are 56 instances with 100 client nodes, divided into 6 groups, namely C1, C2, R1, R2, RC1, and RC2. Each client is located in a 100×100 area. However, there is only one depot for each group of instances. In order to make the Solomon instances applicable to the TDGLRP problem, we randomly generate 10 depots within the range [100 100]. The data of 10 depots are shown in TABLE 4, where “NUM” is an abbreviation of number, “cap” is the capacity, “*coord*”

TABLE 4. Depots data.

NUM	cap	coord	costs	NUM	cap	coord	costs
depot1	990	[40 50]	20000	depot6	970	[18 82]	25000
depot2	800	[64 13]	22500	depot1	1000	[63 93]	19000
depot3	900	[35 79]	21000	depot1	910	[85 8]	24500
depot4	850	[44 57]	20500	depot1	930	[11 63]	23500
depot5	840	[29 40]	24000	depot10	780	[37 17]	23000

TABLE 5. Depots time windows.

BEN	Time window	BEN	Time window
C1	[0 1236]	R2	[0 1000]
C2	[0 3390]	RC1	[0 240]
R1	[0 230]	RC2	[0 960]

TABLE 6. Vehicle data.

BEN	C1	C2	R1	R2	RC1	RC2
Vehicle capacity	200	700	200	1000	200	1000
Vehicle costs	800	2700	500	2500	450	2500

is the coordinate, and “costs” is the fixed open cost. In each group of instances, the time windows of the 10 depots are the same (TABLE 5). And the data of all vehicles are shown in TABLE 6 [51]. These experimental instances are named TD-LRPTW.

B. THE TIME-DEPENDENT SPEED FUNCTION

In the TDGLRP, to simulate the urban road conditions and rush hour, the roads are divided into five types, and the total service time is divided into four equal time zones: the morning rush hour S1, the evening rush hour S3 and two off-rush hours S2 and S4. The road type is judged by equation (26), where $Grade(i,j)$ is the type of road between nodes i and j , and $Mod(a, b)$ is the remainder of the number a divided by the number b . For example, the type of the road between node 2 and node 5 is 3. The speed of each type of road at different time zones is shown in TABLE 7. For example, the speed is 1.8 if the vehicle is driving on the road 1 within the zone S1.

$$Grade(i, j) = Mod((i + j), 5) + 1 \quad (25)$$

TABLE 7. Speed time dependent functions.

Road types	Speed in S1	Speed in S2	Speed in S3	Speed in S4
1	1.80	2.20	1.60	2.40
2	1.60	2.40	1.80	2.20
3	1.40	2.60	1.00	3.00
4	1.20	2.80	1.40	2.60
5	1.00	3.00	1.20	2.80

C. INITIAL SOLUTION

The initial solution is critical to the quality of the final solution. The initial solution generation process includes

two steps: selecting the depots and arranging the routes. First, the 10 depots are sorted according to the center of gravity method. After selecting the first depot, the clients are assigned to this depot according to the construction algorithm. When the capacity of the distribution center is exceeded, the second depot is selected, and so on.

1) DEPOTS SORTING

The sorting steps are as follows:

① Calculating the center coordinates: The center coordinates can be obtained by equation(26), where x_i and y_i are the respective coordinates of client i , and q_i is the demand of client i .

$$X_0 = \frac{\sum_{i=1}^n x_i q_i}{\sum_{i=1}^n q_i}, \quad Y_0 = \frac{\sum_{i=1}^n y_i q_i}{\sum_{i=1}^n q_i} \quad (26)$$

② Calculating the distance matrix: The Euclidean distances between the center and each depot are denoted as DIS_{0j} , which can be obtain by equation (27):

$$DIS_{0j} = \sqrt{(X_0 - x_j)^2 + (Y_0 - y_j)^2} \quad (27)$$

③ After that, the weighted value of each client is obtained by adding the European distance DIS_{0j} , the depot costs FD_j , and the reciprocal of the depot capacity P_j . The depots meeting the constraints will be chosen to open in order of A_j from small to large. The value of A_j is obtained by equation (29), where a_1, a_2 , and a_3 are the coefficients.

$$A_j = a_1 \times DIS_{0j} + a_2 \times FD_j + a_3/P_j, \quad \forall j \in D \quad (28)$$

2) CONSTRUCTION ALGORITHM

In this paper,one construction algorithm is proposed to generate initial solutions. The idea of this algorithm is to insert the clients one by one into the route according to certain conditions until all the clients are inserted into the route. Solomon’s Insertion Algorithm [52] and the IMPACT Algorithm [53] are representative construction algorithms. However, they need to set many coefficients, and different problems need to set different coefficients in order to obtain better solutions. In this paper, we design one algorithm named the Insertion Method based on Travel Time (IMTT) to generate the initial solution. Below we will illustrate the solution process of the initial solution through a simple case. In this case, we assume that there is a depot (named $depot0$) serving five clients (named C_1, C_2, C_3, C_4 and C_5) with time window $[a_i e_i]$.

Proceed as follows:

① First step: Randomly selecting a client node to generate a new route named ROU_1 : $depot0-C_1 -depot0$ (see FIGURE 4(a)).

② Second step: Calculating the travel time TT_{01} from depot0 to C_1 by the method in section 2.2 Therefore, the time when the vehicle arrives at C_1 is $AT_1 = \max(TT_{01}, a_1)$.

③ Third step: Calculating the impact value which equals the total travel time of the new route when new client is

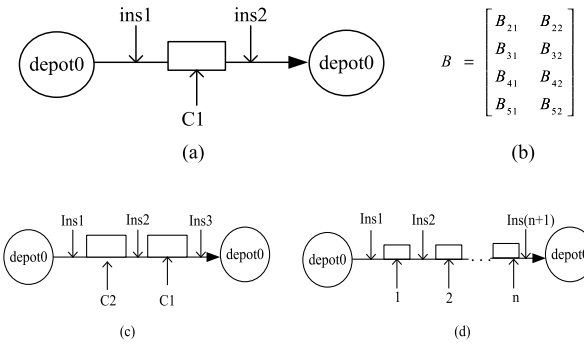


FIGURE 4. Impact value calculation process.

inserted into the original route. The remaining four clients (C_2, C_3, C_4 , and C_5) have two insert positions ($ins1$ and $ins2$) in ROU_1 (see FIGURE 4(a)). The insertion impact value can be represented by matrix B (as shown in FIGURE 4(b)), where B_{ij} represents the total travel time of the new route when the i_{th} client of the remaining clients is inserted into position j . For example, if client C_2 is inserted into the $ins1$ position (i.e., all constraints are met), one new route is obtained: $depot0-C_2 -C_1 -depot0$ (see FIGURE 4(c)). In this case, the impact value B_{11} is equal to the total travel time of the new route. Conversely, if C_2 is inserted into position $ins1$ and the new route does not satisfy the constraint, then B_{11} is equal to inf . According to this method, the values of the other elements in matrix B are obtained. When there are m clients on the route and there are N remaining clients, then then the number of elements in B is $N \times (m + 1)$ (see FIGURE 4(d)).

④ Fourth step: Insertion

The new client is inserted into the current route based on the position of the minimum value in matrix B . For example, if B_{31} is the minimum of B , then client C_3 will be inserted into position $ins1$ of ROU_1 and the new route ROU_1 : $depot0-C_3 -C_1 -depot0$ is obtained (see FIGURE 5).

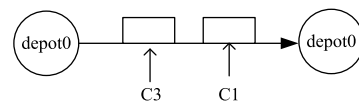


FIGURE 5. The route of ROU1.

⑤ Fifth step: Repeat until all clients are inserted into the route.

D. RESULTS AND ANALYSIS

The program is coded in MATLAB R2018a and executed on a computer with an Intel(R) Core (TM) i5-5200U CPU @2.20GHZ, 4GB of RAM and the Windows 7 operating system.

The depot selection parameters: $a_1 = 100; a_2 = 1, a_3 = \max(P^2)/P_j$, where FD is the costs and P is the capacity of each depot.

The parameters of the HH: $r_k = 0$, iteration = 200.

1) INFLUENCE OF THE INITIAL SOLUTION

In this section, the initial solutions of C1, which are generated by random method and IMTT algorithm, are compared. Then these initial solutions are further optimized by the HH algorithm. The results are shown in TABLE 8, where “VE” is the number of the vehicles, “TC” is total costs, “CPU” is the computer times.

TABLE 8. Comparison random and IMTT.

BEN	IMTT			RANDOM		
	VE	TC	CPU	VE	TC	CPU
C101	11	50402	3.28	35	134281	1.25
C102	11	50988	3.12	36	116164	1.36
C103	11	49147	3.15	37	113399	1.78
C104	11	50602	3.28	36	105638	1.57
C105	11	50368	3.35	36	112364	1.48
C106	11	50344	3.42	36	120134	1.96
C107	11	50520	3.18	36	117935	2.02
C108	11	50477	3.60	36	121368	1.78
C109	11	49569	2.98	36	109636	1.75

It is obvious from the TABLE 8 that the solution results of IMTT algorithm is far superior to the random results. This shows that IMTT algorithm is very effective in solving TDGLRP problem.

2) OPTIMIZATION OBJECTIVES COMPARISON

Distances, costs or travel times are often taken as the optimization objectives in the traditional LRP or LRP with time windows. In this section, we will utilize the proposed IMTT and HH algorithm to solve instance C1 with three different objectives and compare the influence of the different optimization objectives on the solution. The three different objectives are $\min(f_3)$ (minimize distance, see equation (5)); $\min(f_4)$ (minimize travel times, see equation (6)); and f (minimize costs including vehicles costs, open depots costs and fuel cost, see equation (2)). The results are shown in the TABLE 9, where “OB” denotes the objective; “BEN” denotes the benchmark name; “DP” denotes the opened depots; “VE” denotes the number of enabled vehicles; “TC” denotes the total costs, which are calculated by $f_1 + f_2$; “FC” denotes the fuel consumption calculated using equation f_2 ; “TI” denotes the travel time obtained using using equation f_4 and “DIS” denotes the travel distances calculated by equation f_4 . The bold fonts indicate the optimal value for the corresponding column.

In the above eight instances, the f objective obtains 4 optimal values in FC, 6 optimal values in TC, 2 optimal values in TI, 4 optimal values in DIS. The $\min(f_4)$ objective obtains 4 optimal values in FC, 2 optimal values in TC, 6 optimal values in TI, 2 optimal values in DIS. The $\min(f_3)$ objective only obtains 2 optimal values in DIS. FIGURE 6 shows the above results.

From the above results, it can be seen that the cost objective and the time objective are competitive. The cost objective can

TABLE 9. The results of C1 under three objectives.

BN	OB	DP	VE	FC	TC	TI	DIS
C101	f_3	1,4	11	1142	50442	9594	964
	f_4	1,4	11	1017	50317	9575	943
	f	1,4	11	1102	50402	9570	927
C102	f_3	1,4	12	1878	51978	10562	1814
	f_4	1,6	11	1957	55757	10222	2000
	f	1,4	11	1688	50988	10277	1722
C103	f_3	1,6	11	1880	54180	10799	1967
	f_4	1,4	12	1838	51938	10473	1863
	f	1,7	11	1347	49147	9822	1587
C104	f_3	1,4	11	1356	50656	10554	1378
	f_4	1,4	11	1398	50698	10278	1426
	f	1,4	11	1302	50602	10519	1488
C105	f_3	1,4	11	1102	50402	9570	927
	f_4	1,4	11	1031	50331	9555	925
	f	1,4	11	1068	50368	10035	933
C106	f_3	1,4	11	1198	50498	9694	1035
	f_4	1,4	11	1071	50371	9599	1036
	f	1,4	11	1034	50344	10220	978
C107	f_3	1,4	11	1245	50545	9661	1073
	f_4	1,3	11	1075	50875	9621	1044
	f	1,4	11	1240	50520	9655	1081
C108	f_3	1,4	11	1200	50540	9641	1073
	f_4	1,9	11	1094	53994	9601	1124
	f	1,4	11	1177	50477	9796	1135

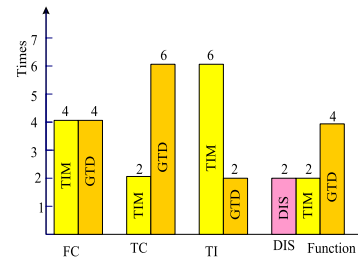


FIGURE 6. Scores of different objectives.

save 2.96% cost than time objective, but it takes 1.74% more travel time. For logistic companies, it is more important to save costs. At the same time, the cost objective takes environmental factors into account. Therefore, the cost objective of TDGLRP proposed in this paper is relatively better.

3) INFLUENCES OF CLIENTS DISTRIBUTION

The Solomon instances have different characteristics, C1 and C2 are cluster, R1, R2 are random, and RC1, RC2 are semi-cluster. FIGURE 7 shows the characteristics of C2 and R2. In this section the influences of client distribution will be analyzed on the solution through C2 and R2 instances. For the sake of fairness, we set all the data (demands, time windows, depots data, vehicles data) of the 100 clients in the R2 to be the same as C2, except for the coordinates. The results, which are calculated under the cost objective, shown in TABLE 10 where $dif = (X_{R1} - X_{C1})/X_{C1}$.

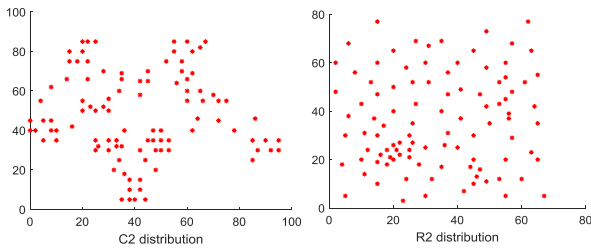


FIGURE 7. Distribution of C2, R2.

TABLE 10. Impact of distribution.

BEN	DP	VE	FC	TC	TI	DIS
C201	4,7	4	709	51009	11364	826
R201	1,5	5	1946	58446	12299	2298
dif1(%)		25	174.47	14.58	8.23	178.21
C202	1,7	4	1080	50800	13433	1309
R202	5,7	5	1871	58371	14138	2248
dif2(%)		25	73.24	12.97	5.25	71.73
C203	4,7	4	1441	51741	13315	1818
R203	7,9	5	1769	57769	16343	2207
dif3(%)		25	22.76	11.65	22.74	21.39
C204	1,7	4	902	50702	12387	1166
R204	1,7	4	1149	50949	13203	1477
dif4(%)		0	27.38	4.88	6.59	26.67

The values of R1 are far greater than C2 according to the results in the TABLE 10. At the same time, more vehicles are needed in C2. That is to say, the clustered client distribution is more conducive to the route arrangement.

4) IMPACT OF TIME WINDOWS

Instances: RC1 and RC2

Hypothesis: All the data (demands, coordinates, depots capacity, depots coordinates and vehicles data) of the clients in the RC2 are same to the RC1, except for the time windows of clients and depots. The results are shown in TABLE 11, where ‘‘TIA’’ is the means of the time windows, ‘‘VE’’ is the number of the vehicles, ‘‘VEA’’ is the means of vehicles, ‘‘TC’’ is the total costs, ‘‘TCA’’ is the means of TC.

TABLE 11. The results of RC1 and RC2.

	RC101	RC102	RC103	RC104	RC201	RC202	RC203	RC204
TIA	30	71	113	155	120	319	518	717
VE	12	12	10	10	10	10	10	10
TC	47591	47538	51579	48342	45566	50461	48988	46969
TCA	48763				46969			
VEA	11				10			

The depot time window of RC1 is [0 240] which is much smaller than the RC2 ([0 960]). The average cost of the RC1 is 48763 and the average vehicle is 11; the average cost of the RC2 is 46969 and the average vehicle is 10. These data suggest that the wider the time window, the fewer vehicles needed and the lower the cost. The narrow time window needs more vehicles to meet the demands of all clients. In the RC1 instances, the average time window of the RC101 is

the smallest, and 12 vehicles need to be activated, while the other 3 groups only need 11 vehicles. The total service time window [0 960] of the RC2 study is far greater than that of the RC1 study, so the four RC2 instances only need to activate 10 vehicles.

5) EXPERIMENTAL RESULTS OF ALL TD-LRPTW

The results of TD-LRPTW are shown in TABLE 12, where CPU is the average computational time.

E. LARGE-SCALE INSTANCES

Homberger [54] has extended the Solomon benchmarks to generate a large-scale instances with 1000 client nodes. In this section, we will use the IMTT and HH algorithm to solve these instances for reference by other researchers. Similarly, in order to adapt Homberger instances to the TDGLRP problem, the data of more depots and vehicles are needed.

1) S-C1-1000 BENCHMARK INSTANCES AND SOLUTIONS

This section calculates the S-C1-1000 benchmarks which includes 10 instances. The data of depots are shown in TABLE 13, where ‘‘coor’’ is coordinates, ‘‘CAP’’ is the capacity. The total service time window of every depot is [0 1824]. Every vehicle capacity is 200 and the cost is 1000. The distribution of clients and depots are shown in FIGURE 8, where blue points are client nodes and red points are the depot nodes. The optimization objective is the total cost f . All the instances run 5 times to get the best value. The results are shown in TABLE 14.

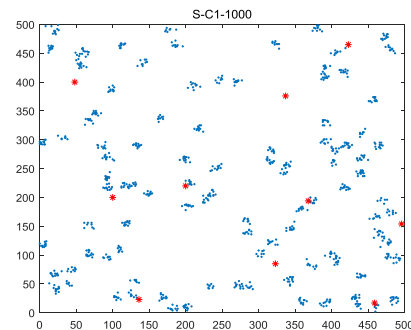


FIGURE 8. Distribution of S-C1-1000.

2) S-C2-1000 BENCHMARK INSTANCES AND SOLUTIONS

The total service time window of every depot is [0 3914] and the other data in the TABLE 13. Every vehicle capacity is 700 and the cost is 2000. The distribution of clients and depots are shown in FIGURE 9, where blue points are client nodes and red points are the depot nodes. The optimization objective is the total cost. All the instances run 5 times to get the best value. The results are shown in TABLE 15.

3) S-R1-1000 BENCHMARK INSTANCES AND SOLUTIONS

The total service time window of every depot is [0 1925] and the other data in the TABLE 13. Every vehicle capacity

TABLE 12. The results of all TD-LRPTW instances.

BN	DP	VE	FC	TC	TI	DIS
C101	1,7	10	1.009.41	87009	9584.82	937.67
C102	4,7	11	2192.35	89992.35	10493.46	2233.04
C103	1,4	11	1339.54	91139.54	10709.35	1525.46
C104	1,3	10	1369.76	91369.76	10953.46	1523.30
C105	1,7	11	1259.93	88059.93	10147.56	1199.68
C106	1,7	11	1198.78	87998.78	10085.95	1150.41
C107	1,7	10	1278.93	87278.93	9739.98	1198.34
C108	1,7	11	1175.14	87975.14	9852.61	1199.80
C109	1,7	10	1359.97	87359.97	9802.20	1497.34
C201	1,4	4	581.42	196381.42	12295.95	658.45
C202	1,4	4	615.92	196415.92	12227.41	728.44
C203	1,4	4	756.48	196556.48	13184.47	1023.62
C204	1,4	4	878.54	196678.54	12418.34	1162.13
C205	1,4	4	547.84	196347.84	10883.46	681.92
C206	1,4	4	538.03	196338.03	10771.98	692.66
C207	1,4	4	560.82	196360.82	11187.38	674.23
C208	1,4	4	603.12	196403.12	11912.75	727.99
R101	1,4	15	1559.84	50059.84	2347.83	1802.59
R102	1,10	14	1683.12	48683.12	2528.57	2127.76
R103	1,10	12	1470.21	47470.21	2248.79	1947.29
R104	1,4	11	1194.01	47694.01	2100.90	1591.06
R105	1,4	12	1388.26	48388.26	1986.74	1711.95
R106	1,4	12	1306.27	48306.27	21836.31	1602.92
R107	1,4	11	1218.38	47718.38	2063.18	1580.43
R108	1,4	9	1044.00	46544.00	1864.20	1365.30
R109	1,4	11	1180.98	47680.98	1761.06	1426.32
R110	1,4	10	1048.46	47048.46	1758.04	1292.94
R111	1,10	11	1269.43	46769.43	1931.16	1595.16
R112	1,4	9	1046.76	46546.76	1671.30	1303.43
R201	6,10	3	1473.40	196973.40	2582.33	1828.31
R202	9,10	3	1332.88	203832.88	2322.78	1.63292
R203	6,9	3	1362.06	199862.06	2161.44	1690.14
R204	1,8	3	840.12	180340.12	2696.70	1230.16
R205	1,8	3	1048.63	180548.63	2415.39	1366.61
R206	1,6	3	1296.72	185796.72	2016.31	1581.26
R207	1,8	3	914.36	180414.36	2149.00	1169.82
R208	1,8	3	856.92	180356.92	2009.68	1190.40
R209	6,9	3	1351.31	199851.31	2025.90	1616.49
R210	1,8	3	1041.77	180541.77	2580.84	1466.50
R211	1,8	3	889.82	180389.82	1768.30	1124.57
RC101	1,3	12	1703.22	42103.22	2108.90	1916.49
RC102	3,8	12	1599.37	42999.37	2146.10	2003.86
RC103	3,8	10	1597.42	420974.29	2093.42	1952.53
RC104	1,2	10	1342.98	42842.98	1949.20	1737.08
RC105	3,8	13	1721.39	43571.39	2141.41	2090.52
RC106	1,2	11	1424.57	43374.57	1915.21	1780.94
RC107	3,7	10	1468.19	45968.19	1881.36	1804.67
RC108	3,8	10	1481.35	41981.35	1909.50	1797.42
RC201	1,8	3	1576.94	189076.94	2440.60	2090.31
RC202	1,8	3	1388.31	188888.31	2744.27	1884.43
RC203	1,8	3	1113.50	188613.50	2278.52	1506.98
RC204	1,8	3	811.30	188311.30	2631.70	1207.94
RC205	1,8	3	1296.92	188796.92	2684.49	1732.35
RC206	1,8	3	1288.10	188788.10	2238.93	1715.19
RC207	1,8	3	1192.49	188692.49	1891.93	1598.48
RC208	1,8	3	1044.97	188544.97	1701.94	1289.95

TABLE 13. The data of S-C1-1000 depots.

NUM	depot1	depot2	depot3	depot4	depot5
coord(x,y)	200,220	423,465	337,376	368,194	323,85
costs	50000	42500	51000	60500	44000
CAP	5990	6800	6900	7850	5840
NUM	depot6	depot7	depot8	depot9	depot10
coord(x, y)	100,200	136,23	48,400	496,154	459,17
costs	55000	59000	44500	53500	53000
CAP	6970	8000	6910	7930	7780

TABLE 14. The results of S-C1-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
C110_1	1,4,5	113	367887	100387	141043	42
C110_2	1,4,5	121	383350	107850	148724	55
C110_3	1,4,5	114	361896	93396	143220	71
C110_4	1,4,5	102	3.31904	7.54046	1.34566	100
C110_5	1,4,5	111	360389	94889	136861	42
C110_6	1,4,5	115	367281	97781	139143	47
C110_7	1,4,5	103	341465	83965	130953	46
C110_8	1,4,5	103	340583	83083	131160	46
C110_9	1,4,5	94	314499	65999	122542	58
C11010	1,4,5	95	314745	65245	122411	61

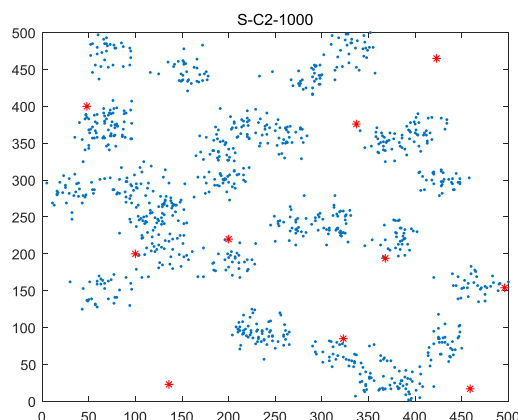


FIGURE 9. Distribution of S-C2-1000.

TABLE 15. The results of S-C2-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
C210_1	1,3,4	31	246861	23361	103905	169
C210_2	1,3,4	33	262420	34920	115881	187
C210_3	1,3,4	36	269602	36102	116448	263
C210_4	1,3,4	34	261358	31858	115379	402
C210_5	1,3,4	32	249767	24267	105931	173
C210_6	1,3,4	32	250663	25163	105334	185
C210_7	1,3,4	34	260882	31382	111432	188
C210_8	1,3,4	32	249460	23960	104067	199
C210_9	1,3,4	33	255605	28105	108702	219
C21010	1,3,4	30	244415	22915	103043	225

is 200 and the cost is 1000. The distribution of clients and depots are shown in FIGURE 10. The results are shown in TABLE 16.

4) S-R2-1000 BENCHMARK INSTANCES AND SOLUTIONS

The total service time window of every depot is [0 7697] and the other data in the TABLE 13. Every vehicle capacity is

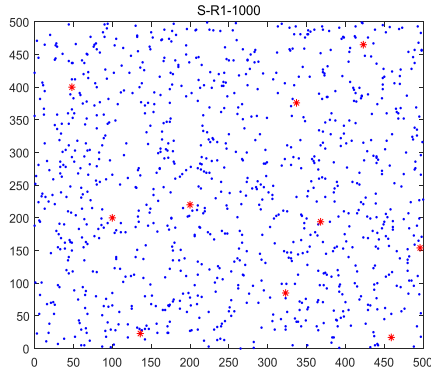


FIGURE 10. Distribution of S-R1-1000.

TABLE 16. The results of S-R1-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
R110_1	1,3,4	105	386676	120176	99524	25
R110_2	1,3,4	108	389585	120085	96709	55
R110_3	1,3,4	104	366808	101308	85721	66
R110_4	1,3,4	100	349420	87920	68900	83
R110_5	1,3,4	101	371220	108720	84296	39
R110_6	1,3,4	100	364107	102607	82733	48
R110_7	1,3,4	98	357204	97704	78091	67
R110_8	1,3,4	99	346332	85832	65019	84
R110_9	1,3,4	96	361932	104432	78896	39
R11010	1,3,4	92	344539	91039	67936	41

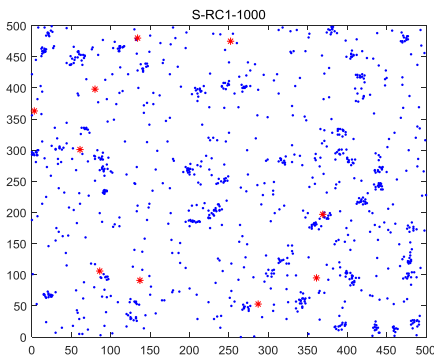


FIGURE 11. Distribution of S-RC1-1000.

TABLE 17. The results of S-R2-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
R210_1	1, 3, 4	24	303707	82207	75356	234
R210_2	1, 3, 4	25	298324	74324	68260	313
R210_3	1, 3, 4	24	283197	61697	61252	423
R210_4	1, 3, 4	23	270016	51016	52362	673
R210_5	1, 3, 4	21	277171	63171	58357	236
R210_6	1, 3, 4	22	277262	60762	54852	271
R210_7	1, 3, 4	22	271433	54933	52458	362
R210_8	1, 3, 4	21	256975	42975	44779	578
R210_9	1, 3, 4	22	281262	64762	61156	251
R21010	1, 3, 4	21	266666	52666	49421	267

1000 and the cost is 2500. The distribution of clients and depots are shown in FIGURE 10. The results are shown in TABLE 17.

5) S-RC1-1000 BENCHMARK INSTANCES AND SOLUTIONS
 For the S-RC1-1000 example, the depot data are shown in TABLE 18. The vehicle capacity is 200 and the cost is 1000. The distribution of clients and depots is shown in FIGURE 11. The optimization goal is the total cost. The results are shown in TABLE 19.

TABLE 18. The data of S-RC1-1000 depots.

NUM	depot1	depot2	depot3	depot4	depot5
coor(x,y)	61,301	369,197	86,106	80,398	252,475
costs	50000	42500	51000	60500	44000
CAP	5990	6800	6900	7850	5840
NUM	depot6	depot7	depot8	depot9	depot10
coor(x,y)	361,95	3,363	287,53	137,91	134,480
costs	55000	59000	44500	53500	53000
CAP	6970	8000	6910	7930	7780

TABLE 19. The results S-RC1-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
RC110_1	2,6,8	111	391302	138302	114360	33
RC110_2	2,6,8	107	373963	124963	101616	42
RC110_3	2,6,8	113	376362	121362	90346	48
RC110_4	2,6,8	94	321710	85710	65360	58
RC110_5	2,6,8	93	343443	108443	96655	36
RC110_6	2,6,8	91	334057	101057	88632	32
RC110_7	2,6,8	92	330247	96247	76809	94
RC110_8	2,6,8	90	317219	85219	64476	100
RC110_9	2,6,8	91	319744	86744	65062	102
RC11010	2,6,8	91	317636	84636	65692	109

6) S-RC2-1000 BENCHMARK INSTANCES AND SOLUTIONS
 the depots data of S-RC2-1000 are shown in TABLE 18 and their time windows are same [0 7284]. Every vehicle capacity is 200 and the cost is 1000. The distribution diagram of clients and distribution centers is shown in FIGURE 11. The results are shown in TABLE 20.

TABLE 20. The results of S-RC2-1000.

BEN	DP	VEH	TI	FC	TI	CPU(S)
RC210_1	2,6,8	21	258223	63723	77134	574
RC210_2	2,6,8	23	264739	65239	78564	634
RC210_3	2,6,8	22	253352	56352	64210	836
RC210_4	2,6,8	26	255252	48252	49360	422
RC210_5	2,6,8	21	251506	57006	82349	227
RC210_6	2,6,8	21	251123	56623	67601	230
RC210_7	2,6,8	21	250156	55656	74585	244
RC210_8	2,6,8	20	242368	50368	60385	252
RC210_9	2,6,8	20	235975	43975	52252	245
RC21010	2,6,8	19	231889	42389	46981	266

V. CONCLUSION

In this paper, the TDGLRP model considering environmental effects is proposed. Its optimization objective is to minimize costs including the fuel consumption costs, opened depot costs and enabled vehicle costs. Unlike the traditional LRP, the TDGLRP model sets the vehicle speed as a time-dependent function in a traffic network. In addition, the traffic network is divided into four periods and five road types. The initial solution is crucial to the convergence and speed of an optimization algorithm. To effectively solve the proposed problem, the IMTT algorithm is structured to generate an initial solution, and then the HH is utilized to optimize the initial solution. The high-level strategy of the HH adopts the TS method to select the low-level pools. The acceptance criterion is to accept all the improved solutions and accept the non-improved solutions with a certain probability. In this paper, 56 instances of the TDGLRP named TD-LRPTW are expanded on the basis of the Solomon benchmarks. These instances with different characteristics are structured to verify the effectiveness of the algorithm and model. The results indicate that the TDGLRP can effectively reduce the fuel consumption and the total costs. The actual urban road network is intricate and time-dependent. The solution results of several large-scale instances are given in Section 5.6 for reference.

AUTHOR CONTRIBUTIONS

C.Z. came up with the main idea of model and algorithm and carried out the simulations. Y.Z. helped with the structure and revisions of the paper. L.L. investigated the state-of-the-art literature and pointed out some suggestions from the literature review.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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