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Highlights

- A carbon pricing initiatives-based bi-level pollution routing problem is studied.
- A model considering an authority and a freight company is developed.
- An integrated interactive solution approach is designed.
- The initiatives impact on freight companies emissions and total cost is analyzed.
- The proposed method can promote freight companies to improve emission performance.

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Carbon pricing initiatives-based bi-level pollution routing problem

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Abstract

The pollution-routing problem aims to route a number of vehicles and determines their speeds on each route segment to minimize total cost, including fuel, emission and driver costs. Recently, carbon pricing initiatives have been widely implemented worldwide. With consideration of the interactions between carbon pricing initiatives and freight schedules, this paper presents a carbon pricing initiatives-based bi-level pollution routing problem involving an authority and a freight company. An interactive solution approach integrating a fuzzy logic controlled particle swarm optimization and a modified adaptive large neighborhood search heuristic is designed to search for solutions for the carbon pricing initiatives-based bi-level pollution routing problem. Computational experiments and analysis are then conducted to shed light on the influence of carbon pricing initiatives on carbon emissions and the total cost of freight companies. In this part, extended models for the carbon pricing initiatives-based bi-level pollution routing problem with a freight company delivering to multiple regions and with multiple freight companies are proposed and computed using the algorithms based on the interactive solution approach. The results indicate that the proposed method can promote freight company improvements in emission performance, and assist authorities in making decisions for road freight transport carbon emission reduction.

Keywords: Transportation, Pollution-routing problem, Carbon pricing initiatives, Modified adaptive large neighborhood search heuristic, Fuzzy logic controlled particle swarm optimization

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1. Introduction

As one of the largest contributors to climate change, which has significant negative effects on the earth, carbon emissions have been an increasing concern to governments and industries (Frölicher, 2016; Hsiang et al., 2017). In 2018, global energy-related carbon emissions reached a historic high of 33.1 gigatons, which was 15.33% higher than the emissions (28.7 gigatons) in 2009 (International Energy Agency, 2019). China, the United States and Europe accounted for 55.29% of global energy-related carbon emissions last year, with 4.9 gigatons, 9.5 gigatons, and 4.0

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gigatons, respectively. Transportation, a significant emitter of carbon dioxide, was responsible for 24% (7.8 gigatons) of global energy-related carbon emissions (32.3 gigatons) in 2016 (International Energy Agency, 2018). As a main part of the transportation sector, road freight transport produces massive carbon emissions, the amount of which is directly proportional to fuel consumption (Demir et al., 2014a; Turkensteen, 2017; Vidal et al., 2019; Duran-Micco et al., 2020). In China, road freight transportation energy consumption accounts for over 30% of the whole transportation sector (396.5 megatons of coal equivalent in 2016), and freight transportation is responsible for about a quarter of the carbon emissions from the transport sector in the United Kingdom and United States (124.5 and 1786.2 megatons of carbon dioxide equivalent in 2016, respectively) (Environmental Protection Agency, 2015; United Kingdom Department for Transport, 2016; NBSC, 2018; OECD, 2019). Over 90% of road freight transport still uses petroleum-based fuels, i.e. gasoline and diesel (Ribeiro et al., 2007; USDOT, 2018). By contrast, the number of electric buses and private cars has been increasing rapidly in recent years (Chung and Kwon, 2015; Pelletier et al., 2016). Therefore, road freight transport may occupy a great share of carbon emissions in the transport sector (Dekker et al., 2012; Bektaş et al., 2018). Thus, curbing road freight transport fuel consumption and carbon emissions is critical for the future development of road freight transport.

In 2011, Bektaş and Laporte (2011) introduced the pollution-routing problem (PRP), an extension of the classical vehicle routing problem (VRP), with time windows to reduce carbon emissions in the road freight transport sector. The PRP minimizes the total cost by routing vehicles to serve a set of customers and determining the speed of each vehicle on each route segment. Since 2011, there have been many extended works for the PRP, including the models and algorithms for the basic PRP and its variants (Toth and Vigo, 2014; Koç et al., 2016; Kellner and Schneiderbauer, 2019; Macrina et al., 2019). Demir et al. (2012) proposed and tested an adaptive large neighborhood search (ALNS) heuristic algorithm for the PRP, and showed that the ALNS could produce significantly better results than the CPLEX. In particular, the CPLEX is intractable for larger instances compared with the ALNS. Franceschetti et al. (2013) introduced the time-dependent PRP by using a two-stage planning horizon from Jabali et al. (2012) for a time-dependent VRP solved via a tabu search procedure. They presented an integer linear programming formulation and studied a special case called the departure time and speed optimization problem. Further, Demir et al. (2014b) considered a bi-objective PRP with the goal of minimizing fuel consumption and driving time, and proposed a bi-objective adaptation of the ALNS heuristic. It is the first study that expands the PRP from a single objective to multiple objectives. Koç et al. (2014) presented the “fleet size and mix PRP” that considered the PRP with heterogeneous vehicle fleets involving different vehicle types for a single objective (minimizing the total cost) to explore the difference between heterogeneous vehicle fleets and homogeneous fleets that only considered one vehicle type. They developed a hybrid evolutionary metaheuristic to solve this problem, demonstrating the benefit of adopting heterogeneous fleets over the homogeneous one. Tajik et al. (2014) investigated the time window pickup-delivery PRP with stochastic vehicle speed, and introduced a robust optimization

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approach to solve this problem. Kramer et al. (2015a) developed an iterated local search-based metaheuristic integrating a speed optimization algorithm (SOA) and a set partitioning formulation for the PRP. Kramer et al. (2015b) designed a novel speed and departure time optimization algorithm to improve the performance of this metaheuristic. Dabia et al. (2016) presented a branch-and-price algorithm-based exact method for a variant of the PRP with specific assumptions concerning the speed on each route and departure time at the depot, and they showed that the method could optimally solve instances with 10 customers. Fukasawa et al. (2016) developed the first arc-based mixed-integer convex program for the PRP with continuous speeds by applying disjunctive convex programming, deriving new valid inequalities for the PRP. Recently, Eshtehadi et al. (2017) designed three different robust optimization approaches for the PRP with demand and travel time uncertainty, showing that uncertainty in terms of demand and travel times could increase fuel consumption. Raeesi and Zografos (2019) studied a new variant of the PRP that considered urban freight distribution operating conditions in the real world and exhibited the trade-off between environmental and business objectives, developing a novel model towards the construction of synthetic driving cycles. Similar to most of these works, this paper studies a variant of the PRP, but there is a significant difference: this paper attempts to reduce road freight transport carbon emissions by considering both the authority and the freight company, while these works only consider the freight company. These works have provided various efficient tools to curb carbon emissions in freight transportation from the freight company's perspective and have inspired this paper to explore useful ways to mitigate road freight transport carbon emissions.

In recent decades, the carbon pricing initiatives have been widely applied in the freight transportation. For example, all papers based on the PRP include carbon prices in their models since the model for the PRP contains a fixed carbon price, which is a consequence of carbon pricing initiatives (IPCC, 2014; World Bank and Ecofys, 2017). Up to 2018, 51 carbon pricing initiatives, involving 70 countries and regions with multiple sectors including freight transportation, have been implemented or are scheduled for implementation, covering 11 gigatons of carbon dioxide equivalent (World Bank and Ecofys, 2018). It can be demonstrated that the implementation of carbon pricing initiatives for the freight transportation are effective ways to achieve road freight transport carbon emission mitigation from the authority's perspective. To jointly curb road freight transport carbon emissions from the perspectives of the authority and the freight company, resolving the conflicts between the authority and the freight company should be put in the first place. Bi-level programming has become a useful method to solve such problems and has been applied in many cases to balance the conflicts between decision makers (Benth et al., 2012; Amideo et al., 2019). It has the ability to allow for all stakeholders in specific problems, such as a public authority and evacuees in an emergency evacuation problem (Yi et al., 2017), an agent and a principal in a moral hazard problem (Ke and Ryan, 2018). The successful use of the bi-level programming in other fields involving multiple stakeholders has motivated this paper to mitigate road freight transport carbon emissions from both the authority's and freight company's perspectives based on the bi-level programming. The

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authority considered in this paper makes carbon pricing initiatives, which include setting a carbon tax price for actual emissions and a carbon subsidy price for carbon emission reduction, to minimize the actual emissions. The freight company makes a freight schedule to minimize the total cost comprising the fuel, emissions, and driver costs. The decisions of the authority and the freight company could influence each other. By considering both the authority and the freight company, the carbon pricing initiatives-based bi-level pollution routing problem (CPIBPRP) is formed.

The contributions of this paper are threefold. The first contribution is to introduce the CPIBPRP as a new variant of the PRP. The second contribution is to propose a bi-level model for the CPIBPRP, and develop an interactive algorithm integrating the fuzzy logic controlled particle swarm optimization (FLCPSO) and the modified ALNS heuristic (IFLCPSO-MALNS) for the bi-level model. The third contribution of our paper is that two extended models are built to depict some existing situations in reality. For example, a freight company usually delivers to multiple regions and there are multiple freight companies under the realm of the authority. These models can be computed by algorithms based on the IFLCPSO-MALNS. Moreover, analyses of results obtained using the CPIBPRP model and extended models are performed to provide managerial insights. These analyses shed light on the influence of carbon pricing initiatives on freight companies' carbon emissions and total cost. They also highlight and quantify the benefits of using carbon pricing initiatives over a fixed carbon tax. The remainder of this paper is organized as follows. Section 2 provides a formal description of the CPIBPRP. The model for the CPIBPRP is constructed in Section 3. A detailed introduction of the IFLCPSO-MALNS is given in Section 4. Section 5 contains computational experiments and analysis. Finally, conclusions, limitations of the study, validation of the heuristic scope, impacts, and future directions are presented in Section 6.

2. Key problem statement

The CPIBPRP is a complex problem for both the freight company and the authority making carbon pricing initiatives towards the road freight transport carbon emission mitigation. The carbon pricing incentives include levying a carbon tax on the freight company and returning carbon subsidies to it according to its mitigation effort in this study. These incentives are based on the carbon tax mechanism, which is one of the mainstream mechanisms for carbon emission reduction worldwide (Anthoff and Tol, 2014; Kök et al., 2016; Yang and Chen, 2018). Basically, the carbon tax mechanism is an application of the Pigovian tax, which is an effective way to correct negative externalities (Pigou, 1929). As road freight transport activities emit carbon dioxide, which is regarded as a key contributor to climate change, the carbon tax mechanism is an effective way to reduce road freight transport carbon emissions (Lin and Li, 2011; Martí et al., 2015). In addition, as a regular approach of industrial policies, the carbon subsidy mechanism is widely applied in various fields (Parry, 1995; Cao et al., 2017). It is usually used for carbon emission reduction in recent years and its ability has been proved to achieve expected targets of decision makers (Kök et al., 2016). Therefore, the

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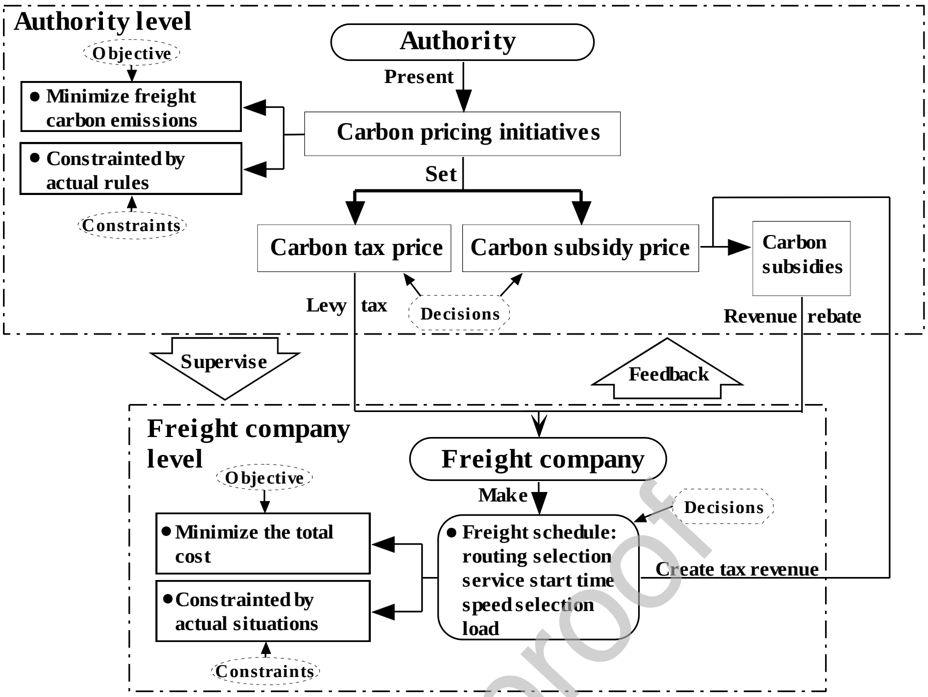

Figure 1: Concept model for the CPIBPRP.

carbon tax incentives that combine the carbon tax mechanism and carbon subsidy mechanism would be helpful for carbon emission reduction in the road freight transport if properly designed.

The CPIBPRP, which is a variant of the PRP, not only considers the freight schedule from the freight company perspective, but also analyzes the carbon pricing initiatives towards the freight company from the authority perspective, involving an interactive relationship between an authority and a freight company, as shown in Fig. 1. From this picture, to minimize the freight company's carbon emissions, the authority makes decisions about carbon pricing initiatives, i.e., setting a carbon tax price and a carbon subsidy price. These decisions will influence the total cost of the freight company, i.e., the objective of the freight company in Fig. 1. The carbon tax price will place an additional cost on the freight company based on its carbon emissions. The freight company will also receive carbon subsidies based on its carbon emission reduction and the carbon subsidy price. As shown in Fig. 1, based on these decisions (i.e., a carbon tax price and a carbon subsidy price) of the authority, the freight company makes its decisions about the freight schedule, including routing selection, service start time, speed selection, and load, to minimize its total cost. Its decisions concerning the freight schedule will determine its carbon emissions, which is the objective of the authority in Fig. 1. Meanwhile, the freight company's decisions will also influence some constraints of the authority based on actual situations. For example, the authority generally does not provide additional money to fund the carbon pricing initiatives (Jenkins, 2014). In other words, the carbon subsidies should not exceed the carbon tax revenue. Moreover, the proportion of carbon-related cost in the total cost should have a threshold for the sustainable development of road

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freight transport (Fahimnia et al., 2013). However, the carbon subsidies, the carbon tax revenue, the carbon-related cost, and the total cost of the freight company will be influenced by its carbon emissions determined by the freight company's decisions. Therefore, the freight company's decisions will influence these constraints of the authority. Therefore, the authority's decisions (i.e., a carbon tax price and a carbon subsidy price) influence the objective (i.e., the total cost) of the freight company, while the freight company's decisions influence the objective (i.e., freight company's carbon emissions) and some constraints of the authority. In other words, the authority and the freight company influence each other through their decisions. In fact, this decision process is similar to a negotiation process, in which all stakeholders hope to reach a consensus, i.e., a satisfactory equilibrium. Consequently, there is a leader-follower relationship, taking account of mutual conflicts and restrictions between an authority and a freight company. Since bi-level programming can effectively describe the leader-follower relationship, a bi-level structure that can reflect the decision process with this relationship, is built. In this structure, as a leader, the authority acting on behalf of the public is on the upper level, with the freight company as a follower on the lower level.

3. Basic model for the CPIBPRP

In this section, the PRP is first described, and then the model for the CPIBPRP is formulated.

3.1. Description of the PRP

The PRP, proposed by Bektaş and Laporte (2011), is defined on a complete directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ with $\mathcal{N}$ as the set of nodes and $\mathcal{A} = \{(i,j) : i, j \in \mathcal{N}, i \neq j\}$ as the set of arcs. Node 0 corresponds to the depot. The distance from i to j is denoted by d_{ij}. A fixed-size fleet of H vehicles is available to serve the nodes and each vehicle has a capacity Q. The set $\mathcal{N}_0 = \mathcal{N}\backslash\{0\}$ is a customer set, and each customer $i \in \mathcal{N}_0$ has a non-negative demand q_i as well as a time interval $[a_i, b_i]$ in which service must start. Early arrivals to customer nodes are permitted but a vehicle arriving early must wait until time a_i before service can start. The service time of customer i is denoted by t_i. The service includes goods/equipment load and unload, handling, and other activities that take place when the vehicle is parked for freight handling purposes (Sánchez-Díaz et al., 2015). The service start means that the vehicle arrives at the customer node and the driver conducts the service. Furthermore, the total time spent on a route in which $j \in \mathcal{N}_0$ is the last visited node before returning to the depot is defined by s_j.

The objective of the PRP is to minimize a total cost function including the driver, fuel and emissions costs. The fuel and emissions costs are related to the fuel consumption, which can be calculated based on the comprehensive emissions model (Barth et al., 2005; Scora and Barth, 2006; Barth and Boriboonsomsin, 2009). According to this model, the instantaneous fuel use rate when traveling at a constant speed v with load f can be estimated as follows:

$$FR = \frac{\xi}{\kappa\psi}(kNV + \frac{0.5C_d A\rho v^3 + (w+f)v(r + g\sin\phi + gC_r\cos\phi)}{1000\varepsilon\varpi}), \tag{1}$$

where ξ is the fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel, ψ is the conversion factor from grams to liters from (g/s) to (l/s), k is the engine friction factor, N is the engine speed, V is the engine displacement, ρ is the air density, A is the frontal surface area, w is the vehicle curb weight, r is the acceleration, g is the gravitational constant, ϕ is the road angle, C_d and C_r are the coefficients of aerodynamic drag and rolling resistance, ε is the vehicle drive train efficiency, and ϖ is the efficiency parameter for diesel engines. Using $\lambda = \xi/\kappa\psi$, $\gamma = 1/1000\varepsilon\varpi$, $\alpha = r+g\sin\phi+gC_r\cos\phi$, $\beta = 0.5C_dA\rho$, Eq. (1) can be simplified to the following:

$$FR = \lambda(kNV + \gamma(\beta v^3 + \alpha(w+f)v)). \tag{2}$$

The total amount of fuel consumption, denoted by F, for traversing a distance d at constant speed v with load f is equal to the fuel rate multiplied by the travel time d/v:

$$F = \lambda(kNV\frac{d}{v} + \gamma\beta d v^2 + \gamma\alpha(w+f)d). \tag{3}$$

Eq. (3) contains three modules in parentheses: the engine module $kNV\frac{d}{v}$, the speed module $\gamma\beta dv^2$, and the weight module $\gamma\alpha(w+f)d$.

From Bektaş and Laporte (2011), a discretized speed function, defined by R non-decreasing speed levels $\bar{v}^r (r \in \mathcal{R} = \{1,\dots,R\})$, is applied. There are then four types of decision variables in the PRP: m_{ij} is a binary variable equal to 1 if and only if a vehicle travels on arc $(i,j) \in \mathcal{A}$; n_j is a non-negative continuous variable representing the time at which service starts at node $j \in \mathcal{N}_0$; l_{ij}^r is a binary variable equal to 1 if arc $(i,j) \in \mathcal{A}$ is traversed at a speed level r; and f_{ij} is a non-negative continuous variable that represents the total amount of flow on each arc (i,j). For the objective (i.e., minimize the total cost) of the freight company, δ is the carbon emission factor of a typical diesel fuel, p_c is a fixed carbon price, p_f is the fuel price, and p_d is the driver wage. There are some other parameters used in constraints. For example, M_{ij} and L are parameters set to constrain time windows. L is a large number, and $M_{ij} = \max\{0, b_i + s_i + d_{ij}/c_{ij} - a_j\}$ (Bektaş and Laporte, 2011; Demir et al., 2012).

The integer linear programming formulation for the PRP is expressed as follows:

$$\begin{aligned}\min f_{PRP} = (p_f + \delta p_c)(&\sum_{(i,j)\in\mathcal{A}} \lambda kNV d_{ij} \sum_{r=1}^{R} l_{ij}^r/\bar{v}^r + \sum_{(i,j)\in\mathcal{A}} \lambda w\gamma\alpha_{ij} d_{ij} m_{ij} + \sum_{(i,j)\in\mathcal{A}} \lambda f_{ij}\gamma\alpha_{ij} d_{ij} \\ &+ \sum_{(i,j)\in\mathcal{A}} \lambda\beta\gamma d_{ij} \sum_{r=1}^{R} l_{ij}^r (\bar{v}^r)^2) + p_d \sum_{j\in\mathcal{N}_0} s_j \quad .\end{aligned} \tag{4}$$

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subject to the following:

$$\sum_{j\in\mathcal{N}} m_{0j} \leq H, \tag{5}$$

$$\sum_{j\in\mathcal{N}} m_{ij} = 1, \forall i \in \mathcal{N}_0, \tag{6}$$

$$\sum_{i\in\mathcal{N}} m_{ij} = 1, \forall j \in \mathcal{N}_0, \tag{7}$$

$$\sum_{j\in\mathcal{N}} f_{ji} - \sum_{j\in\mathcal{N}} f_{ij} = q_i, \forall i \in \mathcal{N}_0, \tag{8}$$

$$q_i m_{ij} \leq f_{ij} \leq (Q - q_i) m_{ij}, \forall (i,j) \in \mathcal{A}, \tag{9}$$

$$n_i - n_j + t_i + \sum_{r=1}^{R} d_{ij} l_{ij}^r / \bar{v}^r \leq M_{ij}(1 - m_{ij}), \forall i \in \mathcal{N}, j \in \mathcal{N}_0, i \neq j, \tag{10}$$

$$a_i \leq n_i \leq b_i, \forall i \in \mathcal{N}_0, \tag{11}$$

$$n_j + t_j - s_j + \sum_{r=1}^{R} d_{j0} l_{j0}^r / \bar{v}^r \leq L(1 - m_{j0}), \forall j \in \mathcal{N}_0, \tag{12}$$

$$\sum_{r=1}^{R} l_{ij}^r = m_{ij}, \forall (i,j) \in \mathcal{A}, \tag{13}$$

$$m_{ij} \in \{0,1\}, \forall (i,j) \in \mathcal{A}, \tag{14}$$

$$f_{ij} \geq 0, \forall (i,j) \in \mathcal{A}, \tag{15}$$

$$n_i \geq 0, \forall i \in \mathcal{N}_0, \tag{16}$$

$$l_{ij}^r \in \{0,1\}, \forall (i,j) \in \mathcal{A}, r \in \mathcal{R}. \tag{17}$$

Eq. (4) represents the total cost, including the cost of fuel consumption, carbon emissions and the driver. Eq. (5) imposes that there are no more than H vehicles. Eq. (6) means that the number of arcs leaving from a customer node must be one. Eq. (7) means that the number of arcs arriving at a customer node must be one. These two equations ensure that each customer is visited exactly once. Only one vehicle is possible on an arc. Eq. (8) describes the balance of the flow. It models the flow as increasing by the amount of demand of each visited customer. Eq. (9) restricts the total load a vehicle carries according to its capacity. Eqs. (10)-(12) are time window constraints. Eq. (10) ensures that the sum of each customer node's vehicle arrival time for an arc, service time and transportation time to its descendant node do not exceed the arrival time of the vehicle at its descendant node. Eq. (11) ensures that the arriving time of the vehicle at each customer node satisfies the time interval in which service must start. Eq. (12) calculates the total driving time for each vehicle. Eq. (13) states that only one speed level is selected for each arc. Finally, Eqs. (14)-(17) are variable specification constraints.

The PRP is NP-hard since it is an extension of the classical VRP. The ALNS heuristic algorithm introduced by

Demir et al. (2012) has been widely applied to solve this problem.

3.2. Programming formulation

The CPIBPRP involves the interactions of the authority and the freight company, as shown in Fig. 1. The authority, which is in the "Authority level", makes its decisions on the carbon tax price and the carbon subsidy price for the freight company. The authority attempts to minimize carbon dioxide emitted by the freight company while meeting some rules in reality. For example, the authority generally does not provide additional money to fund the carbon pricing initiatives, and the carbon tax price (or carbon subsidy price) should have a range limitation. The freight company shown at the "Freight company level" pays for the carbon emissions based on the carbon tax price and receives the carbon subsidies based on the carbon subsidy price and emission reduction. After receiving the information about the carbon tax price and the carbon subsidy price set by the authority, the freight company focuses on total cost minimization with an optimal freight schedule, which must satisfy the actual constraints. The mathematical notations used in this study are listed in Table 1.

As the policy maker of carbon pricing initiatives, the authority makes its decisions to curb the carbon emissions from the freight company. The carbon tax price (i.e. x) and the carbon subsidy price (i.e. y) are key decision variables in the regulation of freight transport networks for the authority. Therefore, the crucial issue for the authority is at what level to set the carbon tax price and the carbon subsidy price. The freight company has to pay for the carbon tax set by the authority, i.e., $\delta x F(m,n,l,f)$, and receives the carbon subsidies based on its carbon emission reduction, i.e., $\delta y(F_I - F(m,n,l,f))$. $F(m,n,l,f)$ represents the fuel consumption of the freight company, i.e., $\sum_{(i,j)\in\mathcal{A}} \lambda kNVd_{ij}\sum_{r=1}^{R} l_{ij}^r/\bar{v}^r + \sum_{(i,j)\in\mathcal{A}} \lambda w\gamma\alpha_{ij}d_{ij}m_{ij} + \sum_{(i,j)\in\mathcal{A}} \lambda\gamma\alpha_{ij}d_{ij}f_{ij} + \sum_{(i,j)\in\mathcal{A}} \lambda\beta\gamma d_{ij}\sum_{r=1}^{R} l_{ij}^r(\bar{v}^r)^2$. F_I is the initial carbon emissions of the freight company, i.e., the original carbon emissions of the freight company, which will be assessed when applying carbon pricing initiatives. Particularly, if the freight company's actual carbon emissions exceed its initial carbon emissions, the carbon subsidies are negative, meaning that the subsidies are turned into a fine for the freight company. In this case, the carbon subsidy price represents a penalty price for the excess carbon emissions. Therefore, the total cost of the freight company under the carbon pricing initiatives made by the authority can be expressed as Eq. (18).

$$f_l = (p_f + \delta x)F(m,n,l,f) + p_d\sum_{j\in\mathcal{N}_0} s_j - \delta y(F_I - F(m,n,l,f)). \tag{18}$$

For the authority who makes the carbon pricing initiatives, its objective is to minimize the freight company's carbon emissions, defined by f_u. It can be calculated by the product of the carbon emission factor and fuel consumption, i.e., $\delta F(m,n,l,f)$. The emissions can be transformed based on Eq. (18), as shown in Eq. (19).

$$f_u = \frac{f_l + \delta y F_I - p_d\sum_{j\in\mathcal{N}_0} s_j}{\frac{1}{\delta}p_f + x + y}. \tag{19}$$

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Table 1: Notations used in the CPIBPRP.

Sets	Description
$\mathcal{N}$	The set of nodes. $i, j \in \mathcal{N}$. $\mathcal{N}_0 = \mathcal{N}\backslash\{0\}$, $\{0\}$ is the depot.
$\mathcal{A}$	The set of arcs. $(i, j) \in \mathcal{A}$.
$\mathcal{R}$	The set of vehicle speed levels. $r \in \mathcal{R} = \{1, 2, \cdots, R\}$.
Decision variables	**Description**
m_{ij}	Binary variables determined by the freight company whether a vehicle travels on arc $(i, j) \in \mathcal{A}$.
n_j	Variable representing the time at which service starts at node $j \in \mathcal{N}_0$, determined by the freight company (s).
l_{ij}^r	Binary variable determined by the freight company whether arc $(i, j) \in \mathcal{A}$ is traversed at a speed level r.
f_{ij}	Variable which represents the total amount of flow on each arc (i, j), determined by the freight company (kg).
x	Carbon tax price, determined by the authority (£/kg).
y	Carbon subsidy price, determined by the authority (£/kg).
Parameters	**Description**
w	Curb weight of a vehicle (kg).
Q	Maximum payload of a vehicle (kg).
ξ	Fuel-to-air mass ratio.
κ	Heating value of a typical diesel fuel (kJ/g).
ψ	Conversion factor from grams to liters (g/l).
k	Engine friction factor of a vehicle (kJ/rev/l).
N	Engine speed of a vehicle (rev/s).
V	Engine displacement of a vehicle (l).
ρ	Air density (kg/m^3).
A	Frontal surface area of a vehicle (m^2).
r	Acceleration of a vehicle (m/s^2).
g	Gravitational constant (m/s^2).
ϕ	Road angle.
C_d	Coefficient of aerodynamic drag of a vehicle.
C_r	Coefficient of rolling resistance of a vehicle.
ε	Vehicle drive train efficiency.
ϖ	Efficiency parameter for diesel engines of a vehicle.
p_f	Fuel price per liter (£).
p_c	Carbon price per kilogram CO_2 (£).
p_d	Driver wage (£/s).
δ	Carbon emission factor of a typical diesel fuel (kg-CO_2/liter).
λ	Function, $\lambda = \xi/\kappa\psi$.
γ	Function, $\gamma = 1/1000\varepsilon\varpi$.
α	Function, $\alpha = r + g\sin\phi + gC_r\cos\phi$.
β	Function, $\beta = 0.5C_dA\rho$.
v	Vehicle speed (m/s).
f	Vehicle load (kg).
H	The number of vehicles that are available.
Q	Capacity of each vehicle.
s_j	Total time spent on a route in which $j \in \mathcal{N}_0$ is the last visited node before returning to the depot (s).
d_{ij}	Distance from i to j (m).
q_i	Demand of customer i (kg).
$[a_i, b_i]$	Time interval in which service must start.
t_i	Service time of customer i (s).
$\bar{v}^r$	Vehicle speed under speed level r (m/s).
c_{ij}	Lower bound of speed limitation on arc (i, j).
M_{ij}	Function, $M_{ij} = \max\{0, b_i + s_i + d_{ij}/c_{ij} - a_j\}$.
L	A large number.
F_I	Initial carbon emissions of the freight company (kg).
C	Maximum proportion of carbon-related cost in the total cost.
C_t	Maximum carbon tax price per kilogram CO_2 (£).
C_s	Maximum carbon subsidy price per kilogram CO_2 (£).

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Generally, the authority does not provide additional money to fund the carbon pricing initiatives (Jenkins, 2014). Thus, the carbon subsidies should not exceed the carbon tax revenue, as shown in Eq. (20).

$$xF(m,n,l,f) - y(F_I - F(m,n,l,f)) \geq 0. \tag{20}$$

For the sustainable development of road freight transport, the proportion of carbon-related cost in the total cost should have a threshold (Fahimnia et al., 2013), as seen in Eq. (21). In this study, the carbon-related cost of the freight company can be expressed as $\delta(x+y)F(m,n,l,f) - \delta y F_I$, and the total cost is $(p_f + \delta x)F(m,n,l,f) + p_d \sum_{j\in\mathcal{N}_0} s_j - \delta y(F_I - F(m,n,l,f))$. For the threshold (i.e., C), it can be predetermined by the authority since the authority can generally determine policy-related parameters when making decisions about carbon pricing initiatives.

$$\frac{\delta(x+y)F(m,n,l,f) - \delta y F_I}{(p_f + \delta x)F(m,n,l,f) + p_d \sum_{j\in\mathcal{N}_0} s_j - \delta y(F_I - F(m,n,l,f))} \leq C. \tag{21}$$

In addition, the carbon tax price and the carbon subsidy price should not less than 0 and have thresholds preset by the authority (Carrara and Longden, 2017), as shown in Eqs. (22) and (23).

$$0 \leq x \leq C_c, \tag{22}$$

$$0 \leq y \leq C_s. \tag{23}$$

By integrating Eqs. (4)-(17) and (18)-(23), the CPIBPRP allowing for the interactive relationship between the authority and the freight company can be formulated as a global model, as shown in Eq. (24). The optimization process of this global model can be outlined. First, based on the objective minimizing the carbon emissions and relevant constraints, the authority presents the carbon pricing scheme for the freight company. The freight company then develops freight transport planning under the carbon pricing initiatives. The freight company's plan is fed back to the authority, which readjusts the carbon tax price and carbon subsidy price in view of the freight company's performance, after which the freight company reconsiders its freight transport planning based on these new prices and develops an improved planning as feedback to the authority. The process is completed after finite repeats that are established in advance. The authority chooses the most satisfactory carbon pricing strategy from all results. By developing the bi-level model (i.e. Eq. (24)) balancing the conflicts between the authority and the freight company, the trade off between the objectives of these decision makers could be determined. For flexible use of this model, it can be adjusted by changing the objective functions (i.e. Eqs. (18) and (19)) and constraints (i.e. Eqs. (4)-(17) and (20)-(23)) based on the actual situation, and additional changes can be made to enhance the applicability for similar situations and identify the most satisfactory decision.

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$$
\min f_u = \frac{f_l + \delta y F_I - p_d \sum_{j\in\mathcal{N}_0} s_j}{\frac{1}{\delta} p_f + x + y}
$$

$$
s.t. \begin{cases}
xF(m,n,l,f) - y(F_I - F(m,n,l,f)) \geq 0, \\
\frac{\delta(x+y)F(m,n,l,f) - \delta y F_I}{(p_f + \delta x)F(m,n,l,f) + p_d \sum_{j\in\mathcal{N}_0} s_j - \delta y(F_I - F(m,n,l,f))} \leq C, \\
0 \leq x \leq C_t, \\
0 \leq y \leq C_s, \\
\text{where } x, y \text{ solve} \\
\min f_l = (p_f + \delta x)F(m,n,l,f) + p_d \sum_{j\in\mathcal{N}_0} s_j - \delta y(F_I - F(m,n,l,f)) \\
s.t. \begin{cases}
\sum_{j\in\mathcal{N}} m_{0j} \leq H, \\
\sum_{j\in\mathcal{N}} m_{ij} = 1, \forall i \in \mathcal{N}_0, \\
\sum_{i\in\mathcal{N}} m_{ij} = 1, \forall j \in \mathcal{N}_0, \\
\sum_{j\in\mathcal{N}} f_{ji} - \sum_{j\in\mathcal{N}} f_{ij} = q_i, \forall i \in \mathcal{N}_0, \\
q_i m_{ij} \leq f_{ij} \leq (Q - q_i) m_{ij}, \forall (i,j) \in \mathcal{A}, \\
n_i - n_j + t_i + \sum_{r=1}^{R} d_{ij} l_{ij}^r / \bar{v}^r \leq M_{ij}(1 - m_{ij}), \forall i \in \mathcal{N}, j \in \mathcal{N}_0, i \neq j, \\
a_i \leq n_i \leq b_i, \forall i \in \mathcal{N}_0, \\
n_j + t_j - s_j + \sum_{r=1}^{R} d_{j0} l_{j0}^r / \bar{v}^r \leq L(1 - m_{j0}), \forall j \in \mathcal{N}_0, \\
\sum_{r=1}^{R} l_{ij}^r = m_{ij}, \forall (i,j) \in \mathcal{A}, \\
m_{ij} \in \{0,1\}, \forall (i,j) \in \mathcal{A}, \\
f_{ij} \geq 0, \forall (i,j) \in \mathcal{A}, \\
n_i \geq 0, \forall i \in \mathcal{N}_0, \\
l_{ij}^r \in \{0,1\}, \forall (i,j) \in \mathcal{A}, r \in \mathcal{R}.
\end{cases}
\end{cases} \tag{24}
$$

The above global model was proposed to solve the CPIBPRP involving an authority and a freight company delivering to one region. In reality, a freight company usually delivers to multiple regions, and there are multiple freight companies under the realm of the authority. Therefore, an extended model for the CPIBPRP with the freight company delivering to multiple regions (CPIBPRPMR) is proposed. Further, an extended model for the CPIBPRP with multiple freight companies (CPIBPRPMFC) is discussed. In the basic PRP, the freight company that delivers multiple regions can optimize its goal in each region based on decisions regarding regions that do not interact with each other. For the CPIBPRP, the decisions of the freight company would be sent to the authority that sets the carbon tax and the carbon subsidy to regulate the operation of the freight company. Therefore, if the freight company delivers to multiple regions, all the regions should be considered in the CPIBPRP, which is the CPIBPRPMR. Further, when the authority makes carbon pricing initiatives, it usually implements the same initiatives in a large area. Generally, there are multiple freight companies in this area. Since the authority makes decisions to minimize the total carbon emissions from all the freight companies based on the feedbacks from these companies, all the freight companies should be considered, i.e., the CPIBPRPMFC. The details of the models for the CPIBPRPMR and the CPIBPRPMFC are presented in Supplementary Material (Appendix A).

4. IFLCPSO-MALNS

In this section, the IFLCPSO-MALNS is developed to solve the proposed bi-level model for the CPIBPRP. The algorithms based on the IFLCPSO-MALNS to solve the models for the CPIBPRPMR and the CPIBPRPMFC are presented in Supplementary Material (Appendix A).

The proposed model (24) is a mixed-integer bi-level model, which has been shown to be an NP-hard problem that is rarely resolved by any accurate solution approach (Farahani et al., 2013; Long et al., 2014). For the upper level, it consists of nonlinear programming with continuous decision variables. Particle swarm optimization (PSO) has good performance in terms of computational efficiency for continuous nonlinear models (Shi and Eberhart, 1998; Wang and Watada, 2012; Zhen et al., 2016). Compared with other heuristic methods, the PSO has many advantages, such as effective memory, easy implementation, and quick convergence, among others (Esteban, 2001; Grobler et al., 2010; Sethanan and Neungmatcha, 2016; Soares et al., 2019). Therefore, a PSO-based algorithm was adopted in this paper to solve the upper level in the proposed model. To improve the computation efficiency, the fuzzy logic controller (FLC), which is able to adaptively adjust algorithm parameters to improve the convergence speed and optimization accuracy, is integrated into the PSO, i.e., FLCPSO (Song et al., 1997; Yun and Gen, 2003). Compared with the mixed integer linear programming formulation for the PRP, the lower level in the bi-level model is almost the same, except for its objective, but it is still a mixed integer linear programming. Since the ALNS has better performance for dealing with various vehicle routing problems compared with mixed integer linear programming solvers (e.g., CPLEX and Gurobi) (Demir et al., 2012, 2014b; Koç et al., 2014, 2016; Majidi et al., 2017; Kancharla and Ramadurai, 2019), an ALNS-based algorithm is adopted to resolve the lower level in the proposed model. For algorithm improvement, the ALNS is modified by developing some new removal and insertion operators. Therefore, an interactive heuristic algorithm involving the FLCPSO and the modified ALNS (IFLCPSO-MALNS) is developed to solve the CPIBPRP.

4.1. Framework of the IFLCPSO-MALNS

There are three parts of the framework for the overall IFLCPSO-MALNS: data, the authority level and the freight company level, as shown in Fig. 2. The data part is preparatory work involving the various parameter inputs. The IFLCPSO-MALNS begins from initializations in which the initialization of the freight company level is constructed

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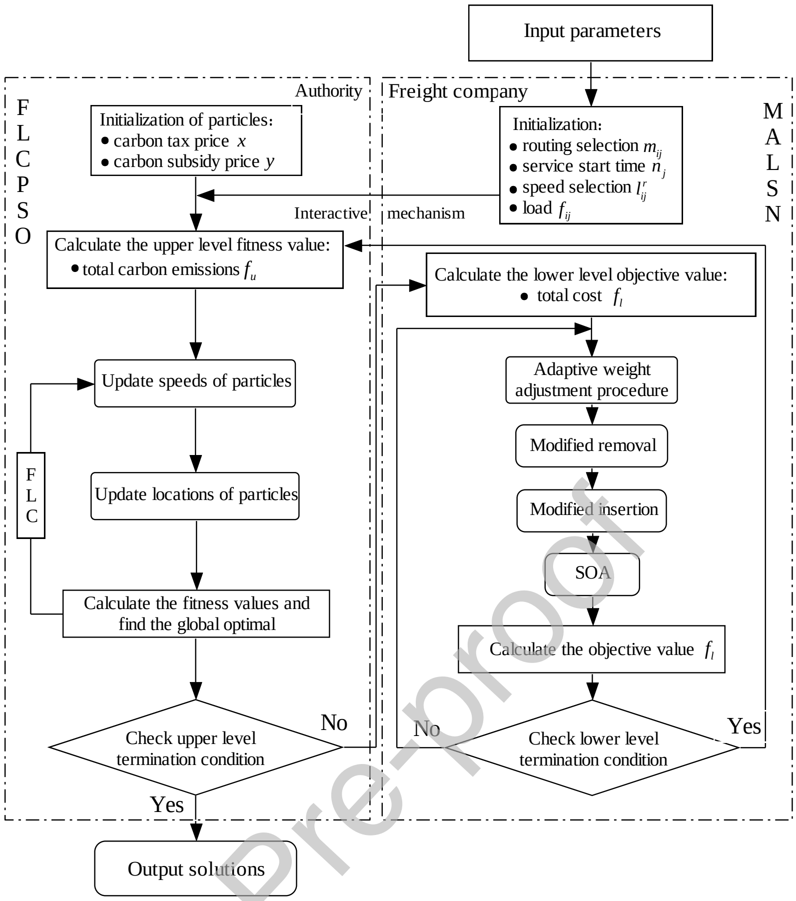

Figure 2: Overall procedure for the IFLCPSO-MALNS.

based on a classical heuristic introduced by Clarke and Wright (1964). The decision variables of the freight company (i.e., routing selection m_{ij}, service start time n_i, speed selection l_{ij}^r and load f_{ij}) are first initialized, followed by the decision variables of the authority (i.e. carbon tax price x and carbon subsidy price y). Seeking for solutions at the authority level starts from the initializations and must meet the constraints (i.e., Eq. (20)-(23)) to guarantee feasibility. When the termination condition of the authority level is not met, the solutions of the authority level are sent to the freight company level to undergo further optimization in consideration of corresponding constraints (i.e. Eq. (4)-(17)) until the termination condition is met. Then, new solutions at the freight company level are generated and input to the authority level. This process continues finite times set by decision makers due to the interactive relationship of the bi-level model solving the conflicts between the authority and the freight company, and the whole procedure effectively simulates the negotiations between these stakeholders. Eventually, final solutions serve as output. The details of the IFLCPSO-MALNS are discussed in the coming sections.

Journal Pre-proof

4.2. FLCPSO for the authority level

In the FLCPSO for the authority level, each particle is presented by x and y. The kth particle $X_k = \{x_k, y_k\}$, $k = 1, \ldots, S$, where S is the size of the swarm and k is the sequence number of particles. Then, Eqs. (25) and (26) are applied to update the velocity and position of each particle (Shi and Eberhart, 1998):

$$v_k(\tau+1) = \omega(\tau)v_k(\tau) + c_p r_p(pbest_k(\tau) - X_k(\tau)) + c_g r_g(gbest(\tau) - X_k(\tau)), \tag{25}$$

$$X_k(\tau+1) = v_k(\tau+1) + X_k(\tau), \tag{26}$$

where τ is the current iteration number, $pbest_k(\tau)$ is the personal best solution of particle k encountered after τ iterations, $gbest(\tau)$ is the global best solution among all particles achieved after τ iterations, r_p and r_g are random numbers between 0 and 1, and $\omega(\tau)$ is the inertia weight used to control the impact of the previous velocities on the current velocity. In addition, c_p and c_g are the acceleration coefficients that determine the relative weights of the global best solution and the personal best solution. These parameters are preset before conducting PSO. $X_k(0)$ and $v_k(0)$ are randomly generated in the feasible solution space (Eberhart and Shi, 2000). For the standard PSO, the inertia weight is calculated as $\omega(\tau) = \omega(T) + \frac{\tau-T}{1-T}(\omega(1) - \omega(T))$, where T is the maximum iteration number.

In this study, FLC is added to the PSO: the inertia weight is tuned based on the difference in the global best solutions in the adjacent two iterations, which is expressed by Eq. (27).

$$\omega(\tau) = (1-\theta)\omega(T) + \frac{\tau - T}{1-T}(\omega(1) - \omega(T)), \tag{27}$$

where θ is determined by the global best solutions in the adjacent two iterations: if $(gbest(\tau-1)/gbest(\tau)) - 1 \geq 0.1$, $\theta = 1$; if $(gbest(\tau-1)/gbest(\tau)) - 1 \leq -0.1$, $\theta = -1$; if $-0.1 < (gbest(\tau-1)/gbest(\tau)) - 1 < 0.1$, $\theta = 0$. Let $gbest(0) = gbest(1)$. If $\omega(\tau) > 1$, let $\omega(\tau) = 1$. It can then increase the search speed when the global best solution is not good, and vice versa. Therefore, the FLCPSO could improve the convergence speed and optimization accuracy. The termination condition for the authority level is that the difference in global best solutions in the adjacent two loops is a very small number (e.g., 10^{-5}); otherwise, the algorithm is terminated when a fixed number of loops is met.

4.3. MALNS for the freight company level

The ALNS, which was introduced by Demir et al. (2012), includes an adaptive weight adjustment procedure, removal operators, insertion operators and a SOA. These removal operators involve the following: random removal (RR), worst-distance removal (WDR), worst-time removal (WTR), route removal (RoR), shaw removal (SR), proximity-based removal (PR), time-based removal (TR), demand-based removal (DR), historical knowledge node removal (HR), neighborhood removal (NR), zone removal (ZR) and node neighborhood removal (NNR). As additional parameters (longitudes and latitudes of nodes) need to be collected when adopting ZR and NNR operators, the preparatory work should require more time. In the MALNS, for the algorithm improvement, two new removal operators are designed to replace the ZR and NNR operators. In the removal phase, s nodes are removed and added to a removal list S.

1. Circle removal (CR)

The circle removal operator chooses a random node first and then removes $s-1$ surrounding nodes based on the distance. In other words, a random node is removed initially, and $s-1$ nodes that have the shortest distances from the first removal node are removed. The worst-case time complexity of the CR operator is $O(n)$.

2. Multiple circle removal (MCR)

This operator chooses multiple random nodes and removes some surrounding nodes. The number of random nodes is determined first: $n_s = \lfloor\sqrt{s}\rfloor$. The first random node and $s-1-\lfloor\frac{s}{n_s}\rfloor(n_s-1)$ surrounding nodes are removed initially, and the next random node and $\lfloor\frac{s}{n_s}\rfloor-1$ surrounding nodes are selected from the remaining nodes. Repeatedly, n_s circles are removed, and almost all circles have $\lfloor\frac{s}{n_s}\rfloor$ nodes except for the first one. The worst-case time complexity of the MCR operator is $O(n^2)$.

For the insertion operators, the ALNS includes the following: greedy insertion (GI); regret insertion (RI); greedy insertion with noise function (GIN); regret insertion with noise function (RIN); zone insertion (ZI). In this section, two new insertion operators are developed. The insertion phase inserts s nodes from the removal list S.

1. Greedy insertion with least time (GILT)

This operator randomly chooses a node $i \in N\backslash S$, for this node the insertion cost based on the increment of the distance is defined as $D_{ij} = d_{ij} + d_{jk} - d_{ik}$, for $j \in S$, $k \in N_0\backslash S$. Additionally, the time function for the least service start time in the time interval of each customer node is calculated as $T_{ij} = n_i + t_i + d_{ij}/c_{ij} - a_j$. This operator then selects the node with the least non-negative time from the least cost to the $\lfloor\sqrt{s}\rfloor$th least cost insertion nodes $j \in S$. Repeatedly, all the nodes $j \in S$ are inserted. The worst-case time complexity of the GILT operator is $O(n^2)$.

2. Regret insertion with least time (RILT)

Let Δf_{ju} denote the change in the objective value for the insertion of node j at its best feasible position on the uth best route. The regret value is calculated as $r_j = \Delta f_{j2} - \Delta f_{j1}$. This operator randomly chooses a node $i \in N\backslash S$. The node with the least non-negative time by using the time function in GILT is then selected from the least cost to the $\lfloor\sqrt{s}\rfloor$th least cost insertion nodes $j \in S$. Repeatedly, all the nodes $j \in S$ are inserted. The worst-case time complexity of the RILT operator is $O(n^3)$.

Similar to the SOA, which runs in two stages in ALNS from Demir et al. (2012), the SOA in this paper is also based on the mathematical model of the speed optimization problem (SOP). However, the objective function is different since it involves carbon subsidies and the carbon price is not a fixed parameter. Therefore, the optimal speeds input to the SOA are partially different. The SOP is defined on a feasible path $(0, \ldots, n+1)$ of nodes that are all served by a single

Journal Pre-proof

vehicle, where 0 and $n+1$ are the same depot. The formulation of SOP in this paper is as follows:

$$\min \sum_{i=0}^{n}(p_f+\delta x)F_i(v_i)+p_d g_{n+1}-\sum_{i=0}^{n}\delta y(F_I-F_i(v_i)) \tag{28}$$

subject to

$$g_{i+1}=g_i+h_i+t_i+d_i/v_i, i=0,\ldots,n, \tag{29}$$

$$a_i \leq g_i+h_i \leq b_i, i=1,\ldots,n, \tag{30}$$

$$v_i^l \leq v_i \leq v_i^u, i=0,\ldots,n, \tag{31}$$

$$g_i \geq 0, i=1,\ldots,n, \tag{32}$$

$$h_i \geq 0, i=1,\ldots,n+1, \tag{33}$$

$$v_i \geq 0, i=1,\ldots,n, \tag{34}$$

$$g_0=h_0=t_0=0, \tag{35}$$

where g_i is the arrival time at node i, h_i is the waiting time at node i, v_i is the speed at which a vehicle travels between nodes i and $i+1$, $[v_i^l, v_i^u]$ is the speed interval between nodes i and $i+1$, and $F_i(v_i)$ is the total fuel consumption derived in Eq. (3) with some specific parameters (e.g., the load f_i, the acceleration r_i and the road angle ϕ_i) of each arc $(i, i+1)$.

To apply the SOA, the convexity of the objective function (28) in the freight company level should be shown.

Proposition 1. The objective function (28) is convex.

Proof. Based on Eqs. (29) and (35), $g_{n+1}=\sum_{i=0}^{n}(h_i+t_i+d_i/v_i)$. Then the objective function (28) can be expressed as follows: $\sum_{i=0}^{n}((p_f+\delta x)F_i(v_i)-\delta y(F_I-F_i(v_i)))+p_d\sum_{i=0}^{n}(h_i+t_i+d_i/v_i)=\sum_{i=0}^{n}((p_f+\delta x)F_i(v_i)-\delta y(F_I-F_i(v_i))+p_d(h_i+t_i+d_i/v_i))$. Let $G_i(v_i)=(p_f+\delta x)F_i(v_i)-\delta y(F_I-F_i(v_i))$ and $H_i(v_i)=p_d(h_i+t_i+d_i/v_i)$ for $i=1,\ldots,n$. Since $\frac{d^2G_i(v_i)}{d(v_i)^2}=(p_f+\delta x+\delta y)(2kNVd_i/v_i^3+2\beta\lambda\gamma d_i)>0$ and $\frac{d^2H_i(v_i)}{d(v_i)^2}=2p_d d_i/v_i^3>0$, $G_i(v_i)$ and $H_i(v_i)$ are convex functions. Since the sum of convex functions is convex, the objective function (28) is convex. □

Proposition 2. The optimal speed v_i^*, which minimizes the total cost on arc $(i, i+1)$ is as follows:

$$v_i^*=\left(\frac{kNV}{2\beta\gamma}+\frac{p_d}{2\beta\lambda(p_f+\delta x+\delta y)}\right)^{1/3}. \tag{36}$$

Proof. Let $\frac{d(u_i(v_i)+w_i(v_i))}{dv_i}=(p_f+\delta x+\delta y)(-kNVd_i/v_i^2+2\beta\lambda\gamma d_i v_i)-p_d d_i/v_i^2=0$, then the optimal speed minimizing the total cost is $v_i^* = (\frac{kNV}{2\beta\gamma} + \frac{p_d}{2\beta\lambda(p_f+\delta x+\delta y)})^{1/3}$. □

Therefore, optimal speeds are calculated using (36) for the SOA (more details can be obtained in Demir et al. (2012)). Following Demir et al. (2012), the termination condition of MALNS is that a fixed number of iterations is met, and then the algorithm returns to the best found solution.

Two extended models for the CPIBPRP (i.e., the models for the CPIBPRPMR and CPIBPRPMFC) can be computed by algorithms based on the IFLCPSO-MALNS, whose details are shown in Supplementary Material (Appendix A).

5. Computational experiments and analysis

This section includes computational experiments that were conducted to assess the performance of the proposed method for the CPIBPRP and further analysis based on the CPIBPRP, CPIBPRPMR, and CPIBPRPMFC. The parameter settings and test instances are described first, followed by presentation of the computational results.

Table 2: Parameters used in the CPIBPRP.

Index	Description	Typical values
w	Curb weight of a vehicle (kg)	6350
Q	Maximum payload of a vehicle (kg)	3650
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor from grams to liters (g/l)	737
k	Engine friction factor of a vehicle (kJ/rev/l)	0.2
N	Engine speed of a vehicle (rev/s)	33
V	Engine displacement of a vehicle (l)	5
ρ	Air density (kg/m^3)	1.2041
A	Frontal surface area of a vehicle (m^2)	3.912
r	Acceleration of a vehicle (m/s^2)	0
g	Gravitational constant (m/s^2)	9.81
ϕ	Road angle	0
C_d	Coefficient of aerodynamic drag of a vehicle	0.7
C_r	Coefficient of rolling resistance of a vehicle	0.01
ε	Vehicle drive train efficiency	0.4
ϖ	Efficiency parameter for diesel engines of a vehicle	0.9
p_f	Fuel price per liter (£)	1.2
p_c	Carbon price per kilogram CO_2 (£)	0.027
p_d	Driver wage (£/s)	0.0022
δ	Carbon emission factor of a typical diesel fuel (kg-CO_2/liter)	2.32
C	Maximum proportion of carbon-related cost in the total cost	0.01
C_t	Maximum carbon tax price per kilogram CO_2 (£)	1
C_s	Maximum carbon subsidy price per kilogram CO_2 (£)	1

5.1. Data and experimental setting

The PRP library of Demir et al. (2012) is occupied as the test bed. All instances in this library are from real geographical distances of United Kingdom cities and are available at `http://www.apollo.management.soton.ac.uk/prplib.htm`. In this paper, the sets containing 10 nodes, 50 nodes and 100 nodes are selected as test instances. Each set includes 20 instances, resulting in a total of 60 instances. The carbon price was £0.027/kg-CO_2 suggested by DEFRA

Journal Pre-proof

Journal Pre-proof

(2007) and was estimated as the 'catastrophic' cost by Tol (2005) at £0.060/kg-CO_2 and £0.225/kg-CO_2. Any one of these prices can be used since later calculations do not involve the fixed carbon price. The fuel and emissions price was £1.4/liter from Demir et al. (2012). As the carbon price was £0.027-0.255/kg-CO_2, the fuel price was set at £1.2/liter in this paper. Besides, all the values of CPIBPRP for the freight company level are the same as in Demir et al. (2012). The IFLCPSO-MALNS was implemented in MATLAB. All experiments were conducted on a server with 1.6 gigahertz speed and 4 gigabyte RAM. The parameters used in CPIBPRP are shown in Table 2. For the setting of algorithm parameters, many studies have supplied advice concerning the proper parameters for the PSO. For example, Laskari et al. (2002) suggested that $c_p = c_g = 2$, $w(1) = 1$ and $w(T) = 0.1$ were suitable. Through initial experiments comparing several parameter sets, suitable parameters for the FLCPSO were identified: $S = 60$, $T = N_l = 50$. In addition, the iteration number of the MALNS is the same as in Demir et al. (2012). The heuristic parameters are shown in Table 3.

Table 3: Parameters used in the IFLCPSO-MALNS.

Index	Description	Typical values
S	Population size of the FLCPSO	60
T	Maximum iteration number of the FLCPSO	50
N_A	Iteration number of the MALNS	25000
c_p	Acceleration coefficient of the personal best solution in the FLCPSO	2
c_g	Acceleration coefficient of the global best solution in the FLCPSO	2
$w(1)$	Initial inertia weight in the FLCPSO	1
$w(T)$	Final inertia weight in the FLCPSO	0.1
N_l	Number of loops for the IFLCPSO-MALNS	50

5.2. Results for the CPIBPRP

The parameter values shown in Tables 2 and 3 are the input for the IFLCPSO-MALNS. The initial carbon emissions (i.e. F_I) are difficult to collect since the test instances are from `http://www.apollo.management.soton.ac.uk/prplib.htm`. Therefore, carbon emissions calculated by the PRP without a carbon tax are used as the benchmark in this paper. The total cost of the PRP without a carbon tax can also be determined when calculating the initial carbon emissions. The performance of the proposed method can then be determined based on the difference between the computational results from the CPIBPRP and the PRP without a carbon tax. Tables 4-6 show the computational results for the instances with 10 nodes, 50 nodes and 100 nodes, respectively. For each instance, initial carbon emissions (ICE), initial total cost (ITC), carbon tax price (CTP), carbon subsidy price (CSP), number of vehicles (NV), total carbon emissions (TE), total cost (TC), percentage decrease in total carbon emissions as a result of using proposed carbon pricing initiatives (Dev_{TE}), and percentage decrease in total cost as a result of using proposed carbon pricing initiatives (Dev_{TC}), are presented. Tables 4-6 show that the percentage decrease in total carbon emissions and the percentage increase in total cost as a result of using the proposed method are 4.61%-8.82% and 3.07%-5.77%, respectively. As shown in Fig. 3, the changes in the averages of Dev_{TE} and Dev_{TC} in CPIBPRP instances with 10 nodes, 50 nodes and

100 nodes are tiny, and these averages are nearly 6.4% and -4%, respectively. In addition, the carbon subsidy price is 0.9913-1.0000 £/kg-CO_2 and the carbon tax price is 0.0564-0.1062 £/kg-CO_2. It is notable that the sum of the carbon tax price and the carbon subsidy price is greater than 1.05£/kg-CO_2, i.e. 2.436 £ per liter fuel consumption, which is more than twice as much as the fuel price. Thus, the impact of the carbon tax price and the carbon subsidy price on cost is twice as high compared with the fuel price, although the maximum proportion of carbon-related cost in the total cost (1%) set in this section seems miniscule. In contrast, the carbon tax price seems fairly high compared with the regular price (0.027 £/kg-CO_2), but the proportion of carbon-related cost in total cost is not greater than 1%.

Table 4: Computational results for the 10-node CPIBPRP instances.

Instances	ICE (kg)	ITC (£)	CTP (£/kg-CO_2)	CSP (£/kg-CO_2)	NV	TE (kg)	TC (£)	Dev_{TE} (%)	Dev_{TC} (%)
UK10_01	170.31	153.83	0.0816	0.9974	2	158.94	162.35	6.68	-5.54
UK10_02	204.57	184.12	0.0849	0.9942	2	190.27	192.98	6.99	-4.81
UK10_03	201.22	180.94	0.0643	0.9993	3	190.83	189.61	5.16	-4.79
UK10_04	189.36	171.27	0.0801	0.9987	2	176.95	177.83	6.55	-3.83
UK10_05	175.15	158.81	0.0777	0.9963	2	164.02	165.11	6.35	-3.96
UK10_06	213.59	193.64	0.0712	0.9995	2	201.25	199.83	5.78	-3.19
UK10_07	189.50	171.60	0.0771	0.9970	2	177.56	178.29	6.30	-3.90
UK10_08	222.47	200.31	0.0898	0.9999	2	206.05	208.74	7.38	-4.21
UK10_09	175.24	157.52	0.1062	0.9906	2	159.78	165.15	8.82	-4.85
UK10_10	189.40	171.17	0.0653	0.9987	2	179.44	176.59	5.26	-3.17
UK10_11	260.07	236.70	0.0726	0.9927	2	244.67	246.01	5.92	-3.93
UK10_12	183.15	165.85	0.0792	0.9957	2	171.25	171.43	6.50	-3.37
UK10_13	196.41	176.41	0.0829	0.9913	2	182.97	186.32	6.84	-5.62
UK10_14	162.76	147.54	0.0741	0.9995	2	152.95	153.24	6.03	-3.87
UK10_15	127.27	114.85	0.0823	0.9995	2	118.70	119.86	6.73	-4.36
UK10_16	185.92	168.19	0.0788	0.9989	2	173.94	174.51	6.44	-3.76
UK10_17	158.53	143.54	0.0962	0.9994	2	146.00	151.83	7.91	-5.77
UK10_18	161.39	146.73	0.0790	0.9944	2	150.92	152.05	6.49	-3.62
UK10_19	169.05	152.71	0.0608	0.9998	2	160.85	158.20	4.85	-3.59
UK10_20	168.79	152.11	0.0806	0.9957	2	157.63	160.18	6.61	-5.30

Table 5: Computational results for the 50-node CPIBPRP instances.

Instances	ICE (kg)	ITC (£)	CTP (£/kg-CO_2)	CSP (£/kg-CO_2)	NV	TE (kg)	TC (£)	Dev_{TE} (%)	Dev_{TC} (%)
UK50_01	607.42	534.95	0.0911	0.9998	7	561.83	559.27	7.50	-4.55
UK50_02	587.69	517.88	0.0686	0.9970	7	554.87	533.76	5.58	-3.07
UK50_03	633.60	557.28	0.0834	0.9925	7	589.85	576.13	6.90	-3.38
UK50_04	663.38	583.63	0.0750	0.9991	8	622.71	607.24	6.13	-4.05
UK50_05	553.08	487.06	0.0806	0.9996	6	516.48	504.82	6.62	-3.65
UK50_06	687.58	606.35	0.0770	0.9950	8	644.07	626.91	6.33	-3.39
UK50_07	572.83	504.39	0.0853	0.9970	7	532.58	529.33	7.03	-4.95
UK50_08	575.28	505.08	0.0732	0.9906	7	540.62	526.10	6.02	-4.16
UK50_09	629.01	554.83	0.0809	0.9995	7	587.25	574.86	6.64	-3.61
UK50_10	639.89	562.71	0.0865	0.9983	7	594.32	590.41	7.12	-4.92
UK50_11	574.37	505.72	0.0714	0.9995	7	540.95	525.17	5.82	-3.85
UK50_12	557.92	492.47	0.0809	0.9995	6	520.86	507.91	6.64	-3.14
UK50_13	617.37	543.95	0.0839	1.0000	7	574.83	570.16	6.89	-4.82
UK50_14	579.81	509.58	0.0855	0.9994	7	539.00	530.84	7.04	-4.17
UK50_15	547.58	483.52	0.0772	0.9973	6	512.98	511.32	6.32	-5.75
UK50_16	568.07	498.84	0.0859	0.9975	6	527.79	517.81	7.09	-3.80
UK50_17	648.41	571.47	0.0777	0.9915	7	606.84	591.72	6.41	-3.54
UK50_18	685.04	603.77	0.0800	0.9959	8	639.97	634.54	6.58	-5.10
UK50_19	604.68	531.19	0.0921	0.9951	7	558.49	547.63	7.64	-3.09
UK50_20	629.54	554.96	0.0837	0.9991	7	586.20	574.72	6.88	-3.56

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To evaluate the IFLCPSO-MALNS, a robustness analysis is first conducted. The test set can be randomly chosen

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Table 6: Computational results for the 100-node CPIBPRP instances.

Instances	ICE (kg)	ITC (£)	CTP (£/kg-CO_2)	CSP (£/kg-CO_2)	NV	TE (kg)	TC (£)	Dev_{TE} (%)	Dev_{TC} (%)
UK100_01	1286.02	1110.45	0.0817	0.9959	14	1198.26	1161.78	6.82	-4.62
UK100_02	1205.75	1046.33	0.0564	0.9936	13	1150.17	1081.86	4.61	-3.40
UK100_03	1129.03	976.81	0.0772	0.9962	13	1056.99	1012.64	6.38	-3.67
UK100_04	1146.13	989.66	0.0814	0.9934	14	1068.13	1020.74	6.81	-3.14
UK100_05	1088.76	936.12	0.0869	0.9953	14	1010.42	969.55	7.20	-3.57
UK100_06	1259.17	1086.40	0.0622	0.9993	14	1195.39	1136.02	5.07	-4.57
UK100_07	1096.59	947.19	0.0820	0.9985	12	1020.97	978.82	6.90	-3.34
UK100_08	1147.03	989.57	0.0839	0.9961	13	1068.18	1031.34	6.87	-4.22
UK100_09	1051.94	908.33	0.0578	0.9987	12	1003.19	938.06	4.63	-3.27
UK100_10	1115.46	963.28	0.0820	0.9946	12	1038.57	997.82	6.89	-3.59
UK100_11	1250.23	1081.95	0.0755	0.9973	15	1173.68	1119.90	6.12	-3.51
UK100_12	1091.58	941.65	0.0844	0.9990	12	1016.11	978.38	6.91	-3.90
UK100_13	1197.90	1034.16	0.0819	0.9987	13	1115.02	1070.14	6.92	-3.48
UK100_14	1308.51	1130.37	0.0608	0.9914	14	1242.66	1178.15	5.03	-4.23
UK100_15	1362.73	1177.05	0.0831	0.9930	15	1269.32	1238.72	6.86	-5.24
UK100_16	1042.60	898.54	0.0841	0.9993	12	970.81	931.29	6.89	-3.64
UK100_17	1329.13	1148.92	0.0722	0.9995	15	1251.30	1200.09	5.86	-4.45
UK100_18	1145.72	989.36	0.0825	0.9979	13	1066.19	1024.81	6.94	-3.58
UK100_19	1083.59	934.65	0.0849	0.9992	13	1006.31	967.99	7.13	-3.57
UK100_20	1306.19	1128.77	0.0729	0.9998	14	1228.15	1173.84	5.97	-3.99

from the instances with 10 nodes, 50 nodes and 100 nodes. The instances tested herein are UK10_02, UK10_13, UK50_04, UK50_19, UK100_02 and UK100_15. For these instances, this algorithm was run with different parameters, including the loop number of IFLCPSO-MALNS, population size of FLCPSO, and maximum iteration number of FLCPSO. The results are listed in Table 7. No relative error exceeded 1% for the different parameter selections, which is also shown in Fig. 4, indicating that the proposed algorithm is robust to the parameter settings.

The results are further calculated and compared with those using CPLEX for the freight company level and standard PSO for the authority level using the interactive evolutionary mechanism, which can be named as IPSO-CPLEX. To run the IPSO-CPLEX on one interface, the CPLEX® for MATLAB, an extension of IBM®ILOG®CPLEX Optimizers in the MATLAB framework, is applied (Chang et al., 2017). The test sets are the instances with 10 nodes. For these instances, IFLCPSO-MALNS and IPSO-CPLEX are run with the same parameters. The results are listed in Table 8. The IFLCPSO-MALNS shows better performance than the IPSO-CPLEX in computational time for most instances, and the deviations are miniscule.

5.3. Extended analysis

Further, the comparative analyses of the results for the CPIBPRP, CPIBPRPMR, and CPIBPRPMFC are conducted, which can be seen in Supplementary Material (Appendix B).

Based on the above results and analyses, some interesting insights can be discerned. First, the results of CPIBPRP show that the freight schedules under carbon pricing initiatives would produce lower carbon emissions with relatively few cost increases. Additionally, although the carbon tax price seems fairly high in comparison to the regular price, the impact of which and the carbon subsidy price on cost is two times higher than the impact of the fuel price, and the proportion of carbon-related cost in the total cost does not exceed 1%. Thus, the carbon pricing initiatives could have a relatively strong influence on freight schedules with minimal related cost, which may be beneficial for road freight carbon

Table 7: Computational results with different parameters of the IFLCPSO-MALNS.

Instances	N_l	N_A	T	ICE (kg)	ITC (£)	CTP (£/kg-CO_2)	CSP (£/kg-CO_2)	NV	TE (kg)	TC (£)	Dev_{TE} (%)	Dev_{TC} (%)
UK10_02	50	40	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	50	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	60	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	40	50	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	50	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	60	50	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	50	24000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	50	25000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
	50	50	26000	204.57	184.12	0.0879	0.9978	2	189.84	193.28	7.20	-4.97
UK10_13	50	40	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	50	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	60	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	40	50	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	50	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	60	50	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	50	24000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	50	25000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
	50	50	26000	196.41	176.41	0.0882	0.9992	2	182.24	186.77	7.21	-5.87
UK50_04	50	40	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	50	50	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	50	60	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	40	50	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	50	50	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	60	50	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	50	50	24000	664.32	583.81	0.0757	0.9919	8	623.16	607.93	6.20	-4.13
	50	50	25000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
	50	50	26000	663.38	583.63	0.0757	0.9920	8	622.19	607.78	6.21	-4.14
UK50_19	50	40	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	50	50	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	50	60	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	40	50	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	50	50	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	60	50	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	50	50	24000	605.93	531.42	0.0930	0.9998	7	559.50	547.43	7.66	-3.01
	50	50	25000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
	50	50	26000	604.68	531.19	0.0930	0.9999	7	558.33	547.25	7.67	-3.02
UK100_02	50	40	25000	1206.01	1046.47	0.0564	0.9936	13	1150.45	1082.06	4.61	-3.40
	50	50	25000	1205.75	1046.33	0.0564	0.9936	13	1150.17	1081.86	4.61	-3.40
	50	60	25000	1204.77	1046.02	0.0564	0.9936	13	1149.23	1081.71	4.61	-3.41
	40	50	25000	1205.89	1046.37	0.0564	0.9936	13	1150.07	1081.59	4.63	-3.37
	50	50	25000	1205.16	1046.11	0.0564	0.9935	13	1149.78	1081.65	4.60	-3.40
	60	50	25000	1204.63	1045.96	0.0564	0.9936	13	1148.92	1081.43	4.62	-3.39
	50	50	24000	1208.16	1047.27	0.0564	0.9936	13	1152.81	1082.49	4.58	-3.36
	50	50	25000	1205.94	1046.38	0.0564	0.9936	13	1150.02	1081.92	4.64	-3.40
	50	50	26000	1204.63	1045.96	0.0564	0.9936	13	1148.92	1081.43	4.62	-3.39
UK100_15	50	40	25000	1363.75	1177.62	0.0831	0.9929	15	1270.73	1239.42	6.82	-5.25
	50	50	25000	1362.73	1177.05	0.0831	0.9930	15	1269.32	1238.72	6.86	-5.24
	50	60	25000	1362.91	1177.18	0.0831	0.9930	15	1269.45	1238.76	6.86	-5.23
	40	50	25000	1362.55	1176.98	0.0831	0.9930	15	1270.01	1238.93	6.79	-5.26
	50	50	25000	1363.00	1177.23	0.0831	0.9930	15	1269.61	1238.85	6.85	-5.23
	60	50	25000	1362.18	1176.40	0.0831	0.9930	15	1268.03	1237.54	6.91	-5.20
	50	50	24000	1364.67	1177.95	0.0831	0.9930	15	1269.95	1238.91	6.94	-5.17
	50	50	25000	1362.61	1177.02	0.0831	0.9930	15	1269.12	1238.26	6.86	-5.20
	50	50	26000	1362.04	1176.31	0.0831	0.9930	15	1268.03	1237.54	6.90	-5.21

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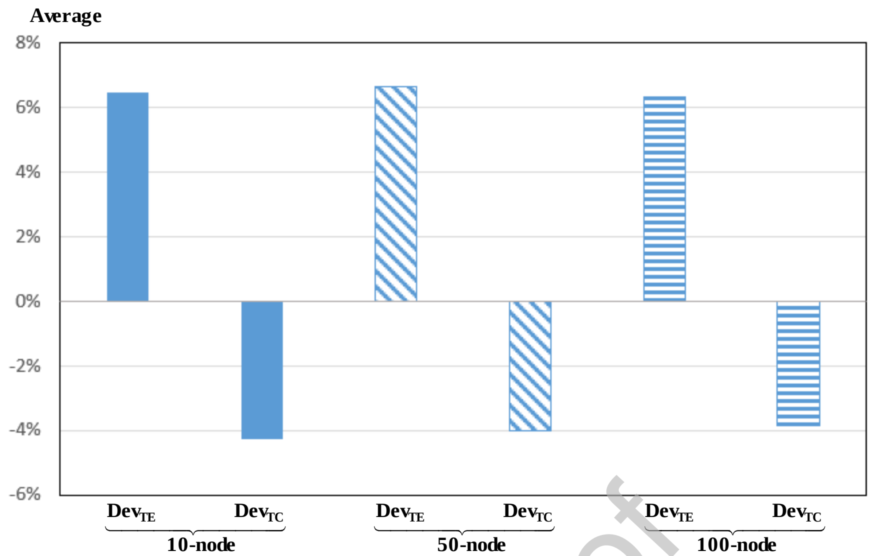

Figure 3: Averages of $\mathrm{Dev}_{\mathrm{TE}}$ and $\mathrm{Dev}_{\mathrm{TC}}$ in CPIBPRP instances with 10 nodes, 50 nodes and 100 nodes.

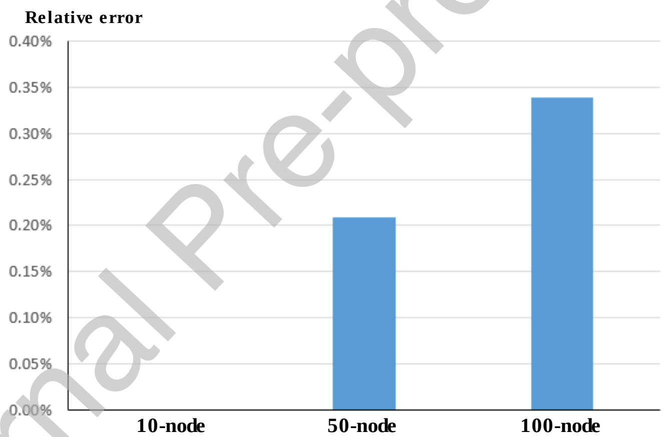

Figure 4: Relative error for different parameter selections in the selected instances with 10 nodes, 50 nodes and 100 nodes.

emission mitigation. Further, based on the results of the CPIBPRPMR and CPIBPRPMFC, unified carbon pricing initiatives would reduce emissions from the most sensitive freight companies. Moreover, by conducting experiments with a fixed carbon price for the CPIBPRPMFC, the benefits of using the proposed carbon pricing initiatives are much greater than those of setting a fixed carbon tax. By analyzing the differences between the effects of the carbon pricing initiatives on the emissions and total cost of the freight companies for the CPIBPRP, CPIBPRPMR, and CPIBPRPMFC, final insights are emerging: although unified carbon pricing initiatives lead to less carbon emission reduction of freight companies, they could curb carbon emissions with relatively few total increases in freight company costs and achieve emission reduction for the most sensitive components in road freight transport. As the amount of carbon emissions is directly proportional to fuel consumption, carbon pricing initiatives also reduce the fuel consumption of freight companies.

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Table 8: Comparative results for IFLCPSO-MALNS with IPSO-CPLEX for instances with 10 nodes.

Instances	IPSO-CPLEX				IFLCPSO-MALNS					Deviations	
	TE (kg)	TC (£)	NV	Total CPU time (s)	TE (kg)	TC (£)	NV	Loop number	Total CPU time (s)	DEV-TE (%)	DEV-TC (%)
UK10_01	158.94	162.35	2	509.5	158.94	162.35	2	3	24.5	0	0
UK10_02	190.27	192.98	2	361.0	190.27	192.98	2	3	25.0	0	0
UK10_03	190.74	189.57	3	2798.4	190.83	189.61	3	3	24.3	-0.05	-0.02
UK10_04	176.95	177.83	2	1209.6	176.95	177.83	2	3	24.8	0	0
UK10_05	164.02	165.11	2	3780.5	164.02	165.11	2	3	25.0	0	0
UK10_06	201.25	199.83	2	1062.7	201.25	199.83	2	3	24.7	0	0
UK10_07	177.56	178.29	2	592.1	177.56	178.29	2	3	26.8	0	0
UK10_08	206.05	208.74	2	438.3	206.05	208.74	2	3	24.5	0	0
UK10_09	159.78	165.15	2	182.0	159.78	165.15	2	3	24.8	0	0
UK10_10	179.44	176.59	2	250.2	179.44	176.59	2	3	25.9	0	0
UK10_11	244.67	246.01	2	171.3	244.67	246.01	2	3	24.8	0	0
UK10_12	171.25	171.43	2	5955.8	171.25	171.43	2	3	24.9	0	0
UK10_13	182.97	186.32	2	3725.1	182.97	186.32	2	3	24.8	0	0
UK10_14	152.95	153.24	2	271.7	152.95	153.24	2	3	25.5	0	0
UK10_15	118.70	119.86	2	1319.2	118.70	119.86	2	3	25.4	0	0
UK10_16	173.94	174.51	2	2062.9	173.94	174.51	2	3	24.0	0	0
UK10_17	146.00	151.83	2	100.3	146.00	151.83	2	3	25.1	0	0
UK10_18	150.92	152.05	2	1586.6	150.92	152.05	2	3	24.8	0	0
UK10_19	160.85	158.20	2	410.8	160.85	158.20	2	4	30.6	0	0
UK10_20	157.63	160.18	2	4116.7	157.63	160.18	2	3	24.3	0	0

6. Conclusions

This paper presented a carbon pricing initiatives-based bi-level pollution routing problem (CPIBPRP), which extended the pollution-routing problem (PRP) introduced by Bektaş and Laporte (2011) to allow for the interaction of the authority and the freight companies by a bi-level model and an IFLCPSO-MALNS. The problem took comprehensive consideration of the stakeholders on the authority and the freight company levels, whose decisions might affect the sustainable development of road freight transport; therefore, it had the ability to assist them in adjusting strategies due to the changes made by others. The authority, who was the carbon pricing initiative maker, played the leading role in the proposed model and the freight company was the follower. The IFLCPSO-MALNS was designed to solve the bi-level model based on the PSO and ALNS. Computational experiments and analysis are then provided, in which extended models for the CPIBPRP with a freight company delivering to multiple regions (CPIBPRPMR) and the CPIBPRP with multiple freight companies (CPIBPRPMFC) are proposed and computed using the algorithms based on the interactive solution approach. The results showed that applying the carbon pricing initiatives could reduce carbon emissions with relatively few increases in the total cost of freight companies, revealing that the proposed method was useful for road freight transport carbon emission reduction. Based on further analyses of the results, some interesting insights were presented, which could help authorities to establish appropriate carbon tax and carbon subsidy prices to curb carbon emissions and assist freight companies in making freight schedules under the carbon pricing initiatives.

There are few limitations of this study. First, only homogeneous fleet of vehicles are considered, but in reality, some fleets of vehicles are heterogeneous. Moreover, this paper considers a single objective for each level, while the authority or the freight company may have multiple objectives in some cases. For validation of the heuristic scope, based on the test of the IFLCPSO-MALNS, this algorithm is valid in the instances with 10, 50 and 100 nodes. This paper

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presents exploratory research on incorporating the decision making of carbon pricing initiatives in pollution routing problems. The CPIBPRP is the first variant of the PRP to consider road freight carbon emission reduction from both the authority's and the freight company's perspectives. It may inspire scholars to conduct relevant studies for the PRP from multiple perspectives and generate novel insights. Moreover, further research is needed. For example, the use of a heterogeneous fleet of vehicles in the CPIBPRP could be an interesting research direction. Another extension would be to consider the impact of path flexibility on the CPIBPRP. In addition, some exact approaches may be designed to solve the CPIBPRP and its extensions.

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References

References

Anthoff, D., Tol, R. S., 2014. Climate policy under fat-tailed risk: an application of FUND. Ann. Oper. Res. 220(1), 223-237.

Amideo, A. E., Scaparra, M. P., Kotiadis, K., 2019. Optimising shelter location and evacuation routing operations: The critical issues. Eur. J. Oper. Res. 279(2), 279-295.

Barth, M., Boriboonsomsin, K., 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transport. Res. Part D 14 (6), 400-410.

Barth, M., Younglove, T., Scora, G., 2005. Development of a heavy-duty diesel modal emissions and fuel consumption model. Technical Report. California Partners for Advanced Transit and Highways (PATH), UC Berkeley.

Bektaş, T., Laporte, G., 2011. The pollution-routing problem. Transp. Res. Part B 45(8), 1232-1250.

Bektaş, T., Ehmke, J. F., Psaraftis, H. N., Puchinger, J., 2018. The role of operational research in green freight transportation. Eur. J. Oper. Res. 274(3), 807-823.

Benth, F. E., Dahl, G., Mannino, C., 2012. Computing optimal recovery policies for financial markets. Oper. Res. 60(6), 1373-1388.

Journal Pre-proof

Cao, K., Xu, X., Wu, Q., Zhang, Q., 2017. Optimal production and carbon emission reduction level under cap-and-trade and low carbon subsidy policies. J. Clean. Prod. 167, 505-513.

Carrara, S., Longden, T. (2017). Freight futures: the potential impact of road freight on climate policy. Transp. Res. Part D 55, 359-372.

Chang, Z., Song, S., Zhang, Y., Ding, J. Y., Zhang, R., Chiong, R., 2017. Distributionally robust single machine scheduling with risk aversion. Eur. J. Oper. Res. 256(1), 261-274.

Chung, S. H., Kwon, C. 2015. Multi-period planning for electric car charging station locations: A case of Korean Expressways. Eur. J. Oper. Res. 242(2), 677-687.

Clarke, G., Wright, J. W., 1964. Scheduling of vehicles from a central depot to a number of delivery points. Oper. Res. 12(4), 568-581.

Dabia, S., Demir, E., Van Woensel, T., 2016. An exact approach for a variant of the pollution-routing problem. Transp. Sci. 1-22.

DEFRA, 2007. The social cost of carbon and the shadow price of carbon: what they are, and how to use them in economic appraisal in the UK. Tech. rep., Department for Environment, Food, and Rural Affairs-Economics Group. <http://www.decc.gov.uk/en/content/cms/what_we_do/lc_uk/valuation/shadow%_price/shadow_price.aspx> (accessed 23.10.2017).

Dekker, R., Bloemhof, J., Mallidis, I., 2012. Operations Research for green logistics-An overview of aspects, issues, contributions and challenges. Eur. J. Oper. Res. 219(3), 671-679.

Demir, E., Bektaş, T., Laporte, G., 2012. An adaptive large neighborhood search heuristic for the pollution-routing problem. Eur. J. Oper. Res. 223(2), 346-359.

Demir, E., Bektaş, T., Laporte, G., 2014a. A review of recent research on green road freight transportation. Eur. J. Oper. Res. 237(3), 775-793.

Demir, E., Bektaş, T., Laporte, G., 2014b. The bi-objective pollution-routing problem. Eur. J. Oper. Res. 232(3), 464-478.

Duran-Micco, J., Vermeir, E., Vansteenwegen, P., 2020. Considering emissions in the transit network design and frequency setting problem with a heterogeneous fleet. Eur. J. Oper. Res. 282(2), 580-592.

Environmental Protection Agency, 2015. Inventory of U.S. greenhouse gas emissions and sinks: 1990-2013. URL: <https://www.epa.gov/sites/production/files/2016-03/documents/us-ghg-inventory-2015-main-text.pdf>.

Journal Pre-proof

Journal Pre-proof

Eberhart, R. C., Shi, Y., 2000. Comparing inertia weights and constriction factors in particle swarm optimization. In Proceedings of the 2000 congress on evolutionary computation. CEC00 (Vol. 1, pp. 84-88). IEEE.

Eshtehadi, R., Fathian, M., Demir, E., 2017. Robust solutions to the pollution-routing problem with demand and travel time uncertainty. Transp. Res. Part D 51, 351-363.

Esteban, P., 2001. Swarm intelligence. Harv. Bus. Rev. 79, 152.

Fahimnia, B., Reisi, M., Paksoy, T., Özceylan, E., 2013. The implications of carbon pricing in Australia: An industrial logistics planning case study. Transp. Res. Part D 18, 78-85.

Farahani, R. Z., Miandoabchi, E., Szeto, W. Y., Rashidi, H., 2013. A review of urban transportation network design problems. Eur. J. Oper. Res. 229(2), 281-302.

Franceschetti, A., Honhon, D., Van Woensel, T., Bektaş, T., Laporte, G., 2013. The time-dependent pollution-routing problem. Transp. Res. Part B 56, 265-293.

Frölicher, T. L., 2016. Climate Response: Strong warming at high emissions. Nat. Clim. Change 6(9), 823-824.

Fukasawa, R., He, Q., Song, Y., 2016. A disjunctive convex programming approach to the pollution-routing problem. Transp. Res. Part B 94, 61-79.

Grobler, J., Engelbrecht, A. P., Kok, S., Yadavalli, S., 2010. Metaheuristics for the multi-objective FJSP with sequence-dependent set-up times, auxiliary resources and machine down time. Ann. Oper. Res. 180(1), 165-196.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., et al., 2017. Estimating economic damage from climate change in the United States. Science 356(6345), 1362-1369.

International Energy Agency, 2018. Transport: Tracking Clean Energy Progress. URL: <https://www.iea.org/tcep/transport/> (accessed 05.05.2019).

International Energy Agency, 2019. Global Energy & CO_2 Status Report The latest trends in energy and emissions in 2018. URL: <https://www.iea.org/geco/emissions/> (accessed 05.05.2019).

IPCC, 2014. Climate Change 2014: Mitigation of Climate Change. Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, UK.

Jabali, O., Woensel, T., De Kok, A. G., 2012. Analysis of travel times and CO_2 emissions in time-dependent vehicle routing. Product. Oper. Manage. 21(6), 1060-1074.

Journal Pre-proof

Jenkins, J. D., 2014. Political economy constraints on carbon pricing policies: What are the implications for economic efficiency, environmental efficacy, and climate policy design? Energy Policy 69, 467-477.

Kancharla, S. R., Ramadurai, G., 2019. Multi-depot Two-Echelon Fuel Minimizing Routing Problem with Heterogeneous Fleets: Model and Heuristic. Netw. Spat. Econ. 1-37.

Ke, R., Ryan, C. T., 2018. Monotonicity of optimal contracts without the first-order approach. Oper. Res. 66(4), 1101-1118.

Kellner, F., Schneiderbauer, M., 2019. Further insights into the allocation of greenhouse gas emissions to shipments in road freight transportation: The pollution routing game. Eur. J. Oper. Res. 278(1), 296-313.

Koç, Ç., Bektaş, T., Jabali, O., Laporte, G., 2014. The fleet size and mix pollution-routing problem. Transp. Res. Part B 70, 239-254.

Koç, Ç., Bektaş, T., Jabali, O., Laporte, G., 2016. Thirty years of heterogeneous vehicle routing. Eur. J. Oper. Res. 249(1), 1-21.

Kramer, R., Subramanian, A., Vidal, T., Cabral, L., 2015a. A matheuristic approach for the pollution-routing problem. Eur. J. Oper. Res. 243(2), 523-539.

Kramer, R., Maculan, N., Subramanian, A., Vidal, T., 2015b. A speed and departure time optimization algorithm for the pollution-routing problem. Eur. J. Oper. Res. 246(2), 782-787.

Kök, A. G., Shang, K., Yücel, Ş., 2016. Impact of electricity pricing policies on renewable energy investments and carbon emissions. Management Science 64(1), 131-148.

Laskari, E. C., Parsopoulos, K. E., Vrahatis, M. N., 2002. Particle swarm optimization for integer programming. In Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600) IEEE. 2: 1582-1587.

Lin, B., Li, X., 2011. The effect of carbon tax on per capita CO_2 emissions. Energy Policy 39 (9), 5137-5146.

Long, J., Szeto, W. Y., Huang, H. J., 2014. A bi-objective turning restriction design problem in urban road networks. Eur. J. Oper. Res. 237(2), 426-439.

Macrina, G., Laporte, G., Guerriero, F., Pugliese, L. D. P., 2019. An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows. Eur. J. Oper. Res. 276(3), 971-982.

Majidi, S., Hosseini-Motlagh, S. M., Ignatius, J., 2017. Adaptive large neighborhood search heuristic for pollution-routing problem with simultaneous pickup and delivery. Soft Comput. 1-15.

Journal Pre-proof

Martí, J. M. C., Tancrez, J. S., Seifert, R. W., 2015. Carbon footprint and responsiveness trade-offs in supply chain network design. Int. J. Prod. Econ. 166, 129-142.

NBSC 2018. China Statistical Yearbook 2018. China Statistics Press, National Bureau of Statistics of China, Beijing.

Yi, W., Nozick, L., Davidson, R., Blanton, B., Colle, B., 2017. Optimization of the issuance of evacuation orders under evolving hurricane conditions. Transp. Res. Part B 95, 285-304.

OECD 2019. Organisation for Economic Co-operation and Development. URL: <https://stats.oecd.org/Index.aspx?DataSetCode=AIR_GHG> (accessed 05.05.2019).

Parry, I.W.H., 1995. Pollution taxes and revenue recycling. J. Environ. Econ. Manage. 29 (3), S64-S77.

Pelletier, S., Jabali, O., Laporte, G., 2016. 50th anniversary invited article-goods distribution with electric vehicles: review and research perspectives. Transp. Sci. 50(1), 3-22.

Pigou, A.C., 1929. The economics of welfare. Macmillan and Company, limited.

Raeesi, R., Zografos, K. G., 2019. The multi-objective Steiner pollution-routing problem on congested urban road networks. Transp. Res. Part B 122, 457-485.

Ribeiro, S.K., Kobayashi, S., Beuthe, M., Gasca, J., Greene, D., Lee, D.S., Muromachi, Y., Newton, P.J., Plotkin, S., Sperling, D., Wit, R., Zhou, P.J., 2007. Transport and its infrastructure. In: Climate Change 2007: Mitigation. URL: <http://www.ipcc.ch/pdf/assessment-report/ar4/wg3/ar4-wg3-chapter5.pdf> (accessed 27.09.2017).

Scora, M., Barth, G., 2006. Comprehensive Modal Emission Model (CMEM), Version 3.01, User Guide. Technical Report. URL: <http://www.cert.ucr.edu/cmem/docs/CMEM_User_Guide_v3.01d.pdf> (accessed 23.10.2017).

Sethanan, K., Neungmatcha, W., 2016. Multi-objective particle swarm optimization for mechanical harvester route planning of sugarcane field operations. Eur. J. Oper. Res. 252(3), 969-984.

Shi, Y., Eberhart, R., 1998. A modified particle swarm optimizer. In Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on. IEEE. pp. 69-73.

Soares, I., Alves, M. J., Antunes, C. H., 2019. Designing time-of-use tariffs in electricity retail markets using a bi-level model-Estimating bounds when the lower level problem cannot be exactly solved. Omega. DOI:10.1016/j.omega.2019.01.005

Song, Y.H., Wang, G.S., Wang, P.Y., Johns, A.T., 1997. Environmental/economic dispatch using fuzzy logic controlled genetic algorithms. Generation, Transm. Distribution, IEEE Proc. IET 144 (4), 377e382.

Journal Pre-proof

Sánchez-Díaz, I., Holguín-Veras, J., Ban, X. J., 2015. A time-dependent freight tour synthesis model. Transp. Res. Part B 78, 144-168.

Tajik, N., Tavakkoli-Moghaddam, R., Vahdani, B., Mousavi, S., 2014. A robust optimization approach for pollution routing problem with pickup and delivery under uncertainty. J. Manuf. Syst. 33(2), 277-286.

Tol, R.S.J., 2005. The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. Energy Policy 33 (16), 2064-2074.

Toth, P., Vigo, D., 2014. Vehicle routing: Problems, methods, and applications. Chapter 15 Green Vehicle Routing. MOS-SIAM Series on Optimization 18. Philadelphia: SIAM. 2nd ed.

Turkensteen, M., 2017. The accuracy of carbon emission and fuel consumption computations in green vehicle routing. Eur. J. Oper. Res. 262(2), 647-659.

United Kingdom Department for Transport, 2016. Motor fuel greenhouse gas reporting: amendments, United Kingdom Department for Transport, United Kingdom. URL: <https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/572984/motorfuel-greenhouse-gas-reporting-regulations-consultation.pdf> (accessed 21.10.2017).

USDOT, 2018. Is Low-Carbon Road Freight Possible? URL: <https://www.itf-oecd.org/low-carbon-road-freight>.

Vidal, T., Laporte, G., Matl, P., 2019. A concise guide to existing and emerging vehicle routing problem variants. Eur. J. Oper. Res.

Wang, S., Watada, J., 2012. A hybrid modified PSO approach to VaR-based facility location problems with variable capacity in fuzzy random uncertainty. Inf. Sci. 192, 3-18.

World Bank, Ecofys, 2017. Carbon Pricing Watch 2017. World Bank, Washington, DC. URL: <http://hdl.handle.net/10986/26565> (accessed 29.10.2017).

World Bank, Ecofys, 2018. State and Trends of Carbon Pricing 2018. World Bank, Washington, DC. URL: <http://documents.worldbank.org/curated/en/480621554812881664/pdf/State-and-Trends-of-Carbon-Pricing-2018.pdf> (accessed 5.5.2019).

Yang, H., Chen, W., 2018. Retailer-driven carbon emission abatement with consumer environmental awareness and carbon tax: Revenue-sharing versus cost-sharing. Omega 78, 179-191.

Yun, Y., Gen, M., 2003. Performance analysis of adaptive genetic algorithms with fuzzy logic and heuristics. Fuzzy Optim Decis Making 2(2), 161-175.

Journal Pre-proof

Zhen, L., Xu, Z., Wang, K., Ding, Y., 2016. Multi-period yard template planning in container terminals. Transp. Res. Part B 93, 700-719.

Journal Pre-proof