On the mathematical modeling of green one-to-one pickup and delivery problem with road segmentation

Abstract

This paper presents a green one-to-one pickup and delivery problem including a set of new features in the domain of green vehicle routing. The objective here is to enhance the traditional models for the one-to-one pickup and delivery problem by considering several important factors, such as explicit fuel consumption (which can be translated into emissions), variable vehicle speed and road categorization (i.e., urban, non-urban). Accordingly, the paper proposes a mixed integer programming model for the problem. A case study from the Netherlands shows the applicability of the model in practice. The numerical analyses show that the investigated factors has a significant impact on operational-level logistics decisions and the selected key performance indicators. The results suggest that the proposed green model can achieve significant savings in terms of total transportation cost. The total cost reduction is found to be (*i*) 3.03% by the use of explicit fuel consumption estimation, (*ii*) up to 10.7% by accounting for variable vehicle speed and (*iii*) up to 10.5% by considering road categorization. As total cost involves explicit energy usage estimation, the proposed model has potential to offer a better support to aid sustainable logistics decision-making process.
Keywords: Pickup and delivery problem, Road segmentation, Greenhouse gas emissions, Energy consumption, Sustainable logistics management

1. Introduction

Logistics is one of the focal sectors in European economy as it contributes to the economic growth and plays a key role in international competitiveness. In the upcoming decades, a steady increase is expected in freight movements throughout Europe mainly due to the population growth and internationalization of trade flows. European Union (EU) policy has been accordingly focusing on improving freight logistics efficiency and mitigating logistics related environmental and social externalities to achieve sustainable logistics (Demir et al., 2015; TRIP, 2015). Apart from several economic goals (e.g., maximizing profit or achieving on-time delivery), sustainable logistics is, therefore, concerned with environmental (e.g., greenhouse gases (GHGs), air pollution, noise pollution, energy use/energy efficiency, renewable energy use, land usage and waste from packaging or shipping) and social (e.g., mobility of citizens, accessibility, employment level and conditions, health and safety incidents) issues as well. Among the aforementioned issues, transportation energy use and GHG emissions are treated as the main key performance indicators (KPIs) in logistics management literature for evaluating sustainability performance of logistics operations (see e.g., Kellner and Igl (2015); Soysal et al. (2012); Soysal (2015); Xiao and Konak (2016); Zhu et al. (2014); Zaman and Shamsuddin (2017).

According to a projection made by the EU on transport sector, oil scarcity and climate change issues are listed as the major challenges of any transport system (Commission, 2011). In this context, the EU has recently adopted a climate and energy package that sets a target of reducing GHG emissions in the EU by 20% with respect to 1990 (Commission, 2009). Private transport sector has the same attitude towards achieving carbon efficient logistics (see e.g., Colicchia et al. (2013)). For instance, the Deutsche Post DHL claims that providing a product or a service to the customer at the right time, at the right cost, at the right place does not mean that your responsibility as a producer or service provider is over (DHL, 2010). The logistics industry should be also responsible for its own environmental impact on human health. According to the company, some of the future trends in sustainable logistics will be as follows: (*i*) CO_2 labeling will become standardized and these labels will allow customers to compare "green" products while making climate-friendly choices (see e.g., Acquaye et al. (2015)), (*ii*) Carbon emissions will have a price tag (see e.g., Choudhary et al. (2015)), and (*iii*) Carbon pricing will lead to more strict regulatory measures (see e.g., Fahimnia et al. (2015)). These developments present the importance of considering more than just economic aspects in current logistics problems.

The vehicle routing problem (VRP) is one of the core problems at operational-level logistics management, since thousands of companies and organizations engaged in the delivery and collection of goods (or people) are confronted with this problem every day (Toth and Vigo, 2014). The classical VRP comprises a vendor (depot) responsible for delivering products to a set of customers and aims to determine vehicle routes of which total travel costs are minimized. The main constraints are as follows (*i*) each customer is visited exactly once, (*ii*) each route starts and ends at the depot, and (*iii*) the total demand of the customers served by a route does not exceed the vehicle capacity.

An important extension of the VRP is named as the VRP with time windows in which service at each customer must start within a given time window. Another related and important extension of the VRP is called as pickup and delivery problem (PDP) in which a set of pickup and delivery requests between location pairs are satisfied. In this study, we address one-to-one PDP with time windows where the objective is to design a set of least cost vehicle routes starting and ending at a common depot in order to satisfy pickup and delivery requests within given time windows, subject to side constraints (Cordeau et al., 2008). In one-to-one

PDP, each origin is associated with a single destination, making up a pickup and delivery (a and b) pair (Şahin et al., 2013). A generic representation of the one-to-one PDP is presented in Figure 1.

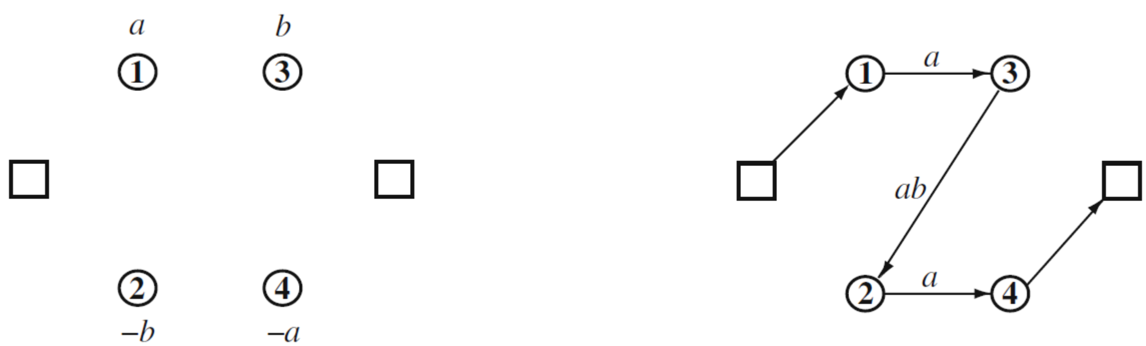

Figure 1: A generic representation of the one-to-one PDP. Vertex label (without sign) means that the vertex supplies commodity; vertex label (-) means that the vertex demands commodity. Arc labels show the commodities carried by the vehicle. Source: Cordeau et al. (2008)

In the VRP literature, the traditional quantitative models for pickup and delivery problems (PDPs) aim to minimize transportation costs with optimal routes for a fleet of vehicles to visit the pickup and drop-off locations in order. The traditional costs often comprise the total distance traveled or total time spent by vehicles (Qu and Bard, 2012). However, we are aware from the green vehicle routing literature that nontraditional green vehicle routing models exploit from the advanced fuel consumption estimation approaches to enhance the environmental sustainability and efficiency of the logistics chain and to better benefit from the real life applications. First, these green models do not rely on only travel distance while estimating fuel consumption, but also consider vehicle load, vehicle speed and other vehicle characteristics. Second, these models often regard travel speed as a decision variable rather than a known parameter, which means that travel speed is not constant and can take any value within given limits. For a detailed information on the studies proposing green models, the interested reader is referred to the reviews by Dekker et al. (2012), Hassini et al. (2012), Erdogan and Miller-Hooks (2012), Lin et al. (2014), or Bektaş et al. (2016). As far as we know, prior to our research, the one-to-one PDP with environmental concerns has not been addressed in the literature.

Apart from these two main concerns addressed in the green VRP literature, traditional models for PDPs assume that roads are homogeneous in every arc. These traditional models, therefore, ignore potential road segmentation in arcs, which can be regarded as a strong assumption in terms of practical implementability in real life. It has been also observed that road categorization is a fact that the green VRP literature tends to overlook.

From this point of view, this paper aims to enhance the traditional one-to-one PDP models, to make them more useful for decision makers in logistics management. In order to achieve this improvement, we develop a decision support model for the one-to-one PDP that accounts for the above mentioned key issues simultaneously. The proposed model accounts for (*i*) an explicit calculation of fuel consumption cost based on travel distance, vehicle load, vehicle speed and other vehicle characteristics, (*ii*) variable vehicle speed that can take any value within given limits, and (*iii*) road categorization as urban and non-urban roads. The enhanced decision support model can be used by decision makers to improve the sustainability performance of the delivery operations in one-to-one PDPs in terms of logistics cost, transportation energy use and carbon emissions. To the best of our knowledge, this is the first attempt to develop a mathematical model for one-to-one PDP with the above mentioned characteristics.

The rest of the paper is structured as follows. Section 2 presents a brief literature review on the topic to highlight the contributions to the related literature. Section 3 presents a formal description of the studied problem, whereas section 4 discusses the proposed decision support model. Section 5 provides computational results on a case study. The last section presents conclusions and future research directions.

2. Related literature review

The PDPs have been attracting the attention of many researchers. We refer to the studies of Berbeglia et al. (2007), Cordeau et al. (2008), Parragh et al. (2008) and Gribkovskaia and Laporte (2008) for literature surveys on the PDPs.

PDP has several practical applications such as courier operations of third party logistics firms (e.g., Şahin et al. (2013)) and maritime cargo operations (e.g., Andersson et al. (2011)). In addition, the well-known Dial-a-Ride Problem (DARP) in the literature is also an application of the PDP, which applies to the transportation of people such as door-to-door transportation for elderly or disabled people (Cordeau and Laporte, 2003). The DARP aims to determine vehicle routes and schedules for a number of users who specify pickup and drop-off requests between origins and destinations (see, e.g., Madsen et al. (1995), Toth and Vigo (1996) and Molenbruch et al. (2017)).

Green vehicle routing is concerned with the incorporation of environmental considerations into operational-level transportation planning. One of the successful implementations in the green vehicle routing is due to Bektaş and Laporte (2011), who have introduced the pollution-routing problem (PRP). In estimating pollution, the authors consider factors such as vehicle speed, vehicle load, and time windows. Their model approximates the total amount of energy consumed on the arc, which directly translates into fuel consumption and further into GHG emissions. Computational results reported by the authors suggest that by using the proposed approach, energy savings can be up to 10% when time windows are in place, and up to 4% when the demand variation is high. The following papers on PRP (e.g., Demir et al. (2012), Franceschetti et al. (2013) , Demir et al. (2014a), Kramer et al. (2015), Koç et al. (2014), Dabia et al. (2016) and Franceschetti et al. (2017)) offer managerial insights on economies of “environmentally friendly” vehicle routing through presenting the tradeoffs among various parameters such as vehicle load, travel speed, vehicle type and mix, and other operational costs (Demir et al., 2014b).

In our literature review, we could not find any such attempt to incorporate environmental concerns into the one-to-one PDP. Some studies on the other variants of the PDPs account for environmental issues. The study of Kumar and Kumar (2015) address PDP with simultaneous pickup and deliveries. The proposed model in this study incorporates simple fuel consumption and emissions estimation based on only travel distance. The authors compare economic and environmental costs associated with different routing schedules. Pan et al. (2015) propose an innovative solution for a PDP based on the idea of using taxis in metropolitan areas to collect and delivery the e-commerce returns from final consumption points back to retailers. The authors discuss the potential economical (pickup and transportation costs), environmental (CO_2 emissions, energy consumption, traffic congestion in city), and social (the wastes of the impulse buying, reduced incitation of online shopping) gains compared to the alternative traditional ways. Dessouky et al. (2003) employ environmental life-cycle impact assessment method to assess the environmental impacts such as pollutant air emissions in a DARP. These impacts are considered in the objective function of the proposed decision support model. Their results show that environmental impacts can be reduced in return for a slight increase in operating costs and in service delays. The study of Marković et al. (2015) on a DARP has demonstrated potential environmental benefit which is obtained through a reduction in total travel distance and travel time due to the use of a new computerized system. Yu et al. (2016) address the DARP of picking up and delivering customers to airport and search for opportunities to reduce carbon emissions from transportation operations. The model that they propose does not respect only travel distance while calculating transportation cost and emissions, but also other factors such as vehicle load and speed. According to their results, significant carbon emission gains could be obtained by means of the enhanced model. Table 1 presents a summary on the reviewed literature on green pickup and delivery problem and green dial-a-ride problem.

Our brief literature review shows that there is a room for improvement in enhancing decision support models for one-to-one PDP. Our study, therefore, adds to the literature on one-to-one PDP by: (i) developing a mixed integer programming formulation for the green one-to-one PDP that takes explicit fuel consumption,

Table 1: Overview of the literature on green pickup and delivery problem and green dial-a-ride problem

Study	Problem	Methodology	Sustainability concern
Kumar and Kumar (2015)	Simultaneous PDP	Mixed-integer linear formulation	Rough transportation energy use calculation
Pan et al. (2015)	Simultaneous PDP	Optimization based simulation	Insights on economical, environmental and social gains
Dessouky et al. (2003)	DARP	Analytical	Life-cycle analysis to analyze environmental impacts
Marković et al. (2015)	DARP	Mixed-integer linear formulation	Insights on emission gain
Yu et al. (2016)	DARP	Analytical	Explicit transportation energy use calculation
This research	one-to-one PDP	Mixed-integer linear and Non-linear programming formulation	Explicit transportation energy use calculation, variable vehicle speed, road categorization

variable vehicle speed and road categorization into account and (*ii*) presenting the applicability of the model on a case study from the Netherlands.

3. Problem description

The problem at hand is defined on a complete directed graph $G = \{V, A\}$, where V is the vertex set and A is the arc set. The vertex set consists of $\{P, D, \{0, 2n+1\}\}$, where $P = \{1, ..., n\}$ is a set of pickup vertices, $D = \{n+1, ..., 2n\}$ is a set of corresponding delivery vertices, and {0,2n+1} refers to the two copies of the depot, serving as the starting and ending points of m vehicle routes. The set of vehicles is denoted by $K = \{1, ..., m\}$, and Q_k refers the capacity of vehicle k. The arc set is defined as $A = \{(i, j) : i = 0, j \in P,$ or $i, j \in P \cup D, i \neq j$ and $i \neq n + j,$ or $i \in D, j = 2n + 1\}$ as in Cordeau et al. (2008).

All delivery requests have to be performed subject to the constraints stating the vertex i is visited before vertex $n + i$ (precedence relationship), and both of these vertices are visited by the same vehicle (pairing relationship). A load q_i is associated for each vertex $i \in V$, satisfying $q_0 = q_{2n+1} = 0, q_i \geq 0$ for $i \in P, q_i = -q_{i-n}$ for $i \in D$. Each vertex $i \in P \cup D$ has a service time $t_i \geq 0$ and a request to be served within a pre-specified time interval $[a_i, b_i]$. If the pre-specified time interval request of any pickup and delivery node has not been satisfied due to either early service or late service, corresponding penalty (time window violation) costs occur.

It is assumed that arcs $(i, j) \in A$ might have urban and non-urban sections in different lengths (distances) denoted as $d^{'}_{ij}$ and $d^{''}_{ij}$ respectively. The speed at which a vehicle travels on arc (i, j) is affected by the road section's traffic regulation.

The defined problem aims to determine the routes of all vehicles by respecting the aforementioned assumptions so as to minimize the total cost of delivery operations that includes fuel consumption costs, driver costs, and penalty costs for breaking time windows constraints. Drivers are paid from the beginning of the time horizon until the time they return to the depot. Traveled distance, vehicle load, vehicle speed and vehicle characteristics are the main factors that affect the fuel consumption in our study.

We estimate the amount of fuel consumption by means of an approach that is based on the comprehensive emissions model of Barth et al. (2005) and Barth and Boriboonsomsin (2009). This approach has also been used in other studies, see e.g., Bektaş and Laporte (2011); Franceschetti et al. (2013); Soysal et al. (2015, 2016).

For vehicle category k, the total amount of fuel used EC_k (liters) for traversing a distance a (m) at constant speed f (m/s) with load F (kg) is calculated through this approach as follows (Soysal et al., 2016):

$$EC_k = \lambda\bigg(y_k(a/f) + \gamma\beta_k a f^2 + \gamma s(\mu_k + F)a\bigg)$$

where $\lambda = \xi/(\kappa\psi)$, $y_k = k_k N_k V_k$, $\gamma = 1/(1000\varepsilon\varpi)$, $\beta_k = 0.5 C_d A_k \rho$, and $s = g\sin\phi + gC_r\cos\phi$.

Furthermore, k_k is the engine friction factor of vehicle category k (kJ/rev/liter), N_k is the engine speed of vehicle category k (rev/s), V_k is the engine displacement of vehicle category k (liter), μ_k is the vehicle curb weight of vehicle category k (kg), g is the gravitational constant (9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, A_k is the frontal surface area of vehicle category k (m^2), ρ is the air density (kg/m^3), ε is the vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines, ξ is the fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s). The reader can be referred to the study of Demir et al. (2011) for further details on these parameters. To estimate corresponding emission (CO_2) levels for transport activities, we use a fuel conversion factor u (kg/l).

4. Formulation of the green one-to-one pickup and delivery problem with road segmentation

This section first presents an integer nonlinear programming formulation for the defined problem, then describes a linear approximation for the nonlinear model. Table 2 presents the notation required for the models.

4.1. A mixed integer nonlinear programming formulation

We present the formulation, starting with the objective function.

Table 2: Parameters and decision variables used in the model

Symbol	Description
P	set of pickup vertices, where $P = \{1, ..., n\}$,
D	set of corresponding delivery vertices, where $D = \{n+1, ..., 2n\}$,
V	set of all nodes including two copies of the depot $\{0, 2n+1\}$, serving as the starting and ending points of all vehicle routes, where $V = \{P \cup D \cup \{0, 2n+1\}\}$,
K	set of vehicles, where $K = \{1, ..., m\}$,
A	set of all arcs, $A = \{(i,j) : i = 0, j \in P,$ or $i, j \in P \cup D, i \neq j$ and $i \neq n+j,$ or $i \in D, j = 2n+1\}$,
q_i	the amount that needs to be picked up from $i \in P$, and delivered to $i+n \in D$, in kg,
t_i	service duration for $i \in V \backslash \{2n+1\}$, in second (s),
Q_k	capacity of vehicle $k \in K$, in kg,
a_i	parameter required for time window restriction for node $i \in P \cup D$, in s,
b_i	parameter required for time window restriction for customer $i \in P \cup D$, in s,
$early_i$	penalty cost per second due to the early arrival to the node $i \in P \cup D$, €/s,
$late_i$	penalty cost per second due to the late arrival to the node $i \in P \cup D$, €/s,
$d^{'}_{i,j}$	total distance needs to be covered in urban section between node i and j, $(i,j) \in A$, in m,
$d^{''}_{i,j}$	total distance needs to be covered in non-urban section between node i and j, $(i,j) \in A$, in m,
λ	technical parameter, $\xi/\kappa\psi$, see section 3,
y_k	technical parameter of vehicle category $k \in K$, $y_k = k_k N_k V_k$, see section 3,
γ	technical parameter, $1/(1000\varepsilon\varpi)$, see section 3,
β_k	technical parameter of vehicle category $k \in K$, $\beta_k = 0.5 C_d A_k \rho$, see section 3,
s	technical parameter, $g \sin\phi + g C_r \cos\phi$, see section 3,
μ_k	curb-weight of vehicle category $k \in K$, in kg,
$price$	fuel price per liter, €/l,
$wage$	wage rate for the drivers of the vehicles, €/s,
$X_{i,j,k}$	binary variable equals to 1 if vehicle $k \in K$ travels on arc $(i,j) \in A$, and 0 otherwise,
$Y_{i,k}$	the time at which vehicle $k \in K$ starts service at node $i \in V \backslash \{2n+1\}$, in s,
$F_{i,j,k}$	the amount of commodity flowing on arc $(i,j) \in A$ by vehicle $k \in K$, in kg,
$U_{i,j,k}$	average vehicle speed of vehicle $k \in K$ between node i and j in urban section, $(i,j) \in A$, (m/s),
$W_{i,j,k}$	average vehicle speed vehicle $k \in K$ between node i and j in non-urban section, $(i,j) \in A$, (m/s),
$S_{i,k}$	the total time spent on a route by vehicle $k \in K$ that has node $i \in D$ as last visited before returning to the depot, in s,
e_i	decision variable required to check early arrival to node $i \in P \cup D$, in s,
l_i	decision variable to check late arrival to node $i \in P \cup D$, in s.

Minimise

$$\underbrace{\sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[y_k\left(\frac{d^{'}_{i,j}}{U_{i,j,k}}X_{i,j,k}\right)+\gamma\beta_k d^{'}_{i,j}\left({U_{i,j,k}}^2 X_{i,j,k}\right)\right]\text{price}}_{\text{nonlinear part}}+\sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[\gamma s(\mu_k X_{i,j,k}+F_{i,j,k})d^{'}_{i,j}\right]\text{price} \tag{1.i}$$

$$+\underbrace{\sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[y_k\left(\frac{d^{''}_{i,j}}{W_{i,j,k}}X_{i,j,k}\right)+\gamma\beta_k d^{''}_{i,j}\left({W_{i,j,k}}^2 X_{i,j,k}\right)\right]\text{price}}_{\text{nonlinear part}}+\sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[\gamma s(\mu_k X_{i,j,k}+F_{i,j,k})d^{''}_{i,j}\right]\text{price} \tag{1.ii}$$

$$+\sum_{k\in K}\sum_{j\in D}S_{j,k}\text{wage} \tag{1.iii}$$

$$+\sum_{i\in P\cup D}(e_i\text{early}_i+l_i\text{late}_i). \tag{1.iv}$$

(1)

The objective function (1) includes four parts: (1.i) fuel consumption cost from transportation operations in urban section, (1.ii) fuel consumption cost from transportation operations in non-urban section, (1.iii) driver cost, and (1.iv) penalty cost for breaking soft time windows.

$$\sum_{k \in K} \sum_{j \in V:(i,j) \in A} X_{i,j,k} = 1, \qquad \forall i \in P \tag{2}$$

$$\sum_{i \in P} X_{0,i,k} = \sum_{i \in D} X_{i,2n+1,k} = 1, \qquad \forall k \in K \tag{3}$$

$$\sum_{j \in V:(i,j) \in A} X_{i,j,k} - \sum_{j \in V:(n+i,j) \in A} X_{n+i,j,k} = 0, \qquad \forall i \in P, k \in K \tag{4}$$

$$\sum_{j \in V:(j,i) \in A} X_{j,i,k} - \sum_{j \in V:(i,j) \in A} X_{i,j,k} = 0, \qquad \forall i \in P \cup D, k \in K \tag{5}$$

$$Y_{i,k} \leq Y_{i+n,k}, \qquad \forall i \in P, k \in K \tag{6}$$

$$\sum_{k \in K} \sum_{j \in V:(j,i) \in A} F_{j,i,k} - \sum_{k \in K} \sum_{j \in V:(i,j) \in A} F_{i,j,k} = -q_i, \qquad \forall i \in P \tag{7}$$

$$\sum_{k \in K} \sum_{j \in V:(j,i) \in A} F_{j,i,k} - \sum_{k \in K} \sum_{j \in V:(i,j) \in A} F_{i,j,k} = q_{i-n}, \qquad \forall i \in D \tag{8}$$

$$F_{i,j,k} - Q_k X_{i,j,k} \leq 0, \qquad \forall (i,j) \in A, k \in K \tag{9}$$

$$\sum_{k \in K} \sum_{i \in P} F_{0,i,k} = 0, \tag{10}$$

$$a_i - e_i \leq Y_{i,k} \leq b_i + l_i, \qquad \forall i \in P \cup D, k \in K \tag{11}$$

$$X_{i,j,k} \left[Y_{i,k} - Y_{j,k} + t_i + \left(\frac{d'_{i,j}}{U_{i,j,k}} + \frac{d''_{i,j}}{W_{i,j,k}} \right) \right] \leq 0, \qquad \forall i,j \in V \backslash \{2n+1\} : (i,j) \in A, k \in K \tag{12}$$

$$X_{j,2n+1,k} \left[Y_{j,k} + t_j - S_{j,k} + \left(\frac{d'_{j,2n+1}}{U_{j,2n+1,k}} + \frac{d''_{j,2n+1}}{W_{j,2n+1,k}} \right) \right] \leq 0, \qquad \forall j \in D, k \in K. \tag{13}$$

Constraints (2) to (4) ensure that each pickup location must be visited once by the same vehicle. Constraints (3) to (5) guarantee that each vehicle starts and ends its route at the depot. Constraints (6) force the vehicle k to visit pickup node first. Constraints (7) and (8) ensure flow conservation at pickup and delivery locations. Constraints (9) mean that vehicle capacities are respected. Constraints (10) mean that vehicles are empty while departing from the depot. Constraints (11) to (12) impose time windows for the vehicles. Note that constraints (12) allow to consider different departure time options from the depot. This means that vehicles do not leave the depot at a predefined time. A vehicle might prefer to leave the depot later in order to not bear the time window violation cost at the first visited node. Constraints (13) are used to calculate the total driving time for each vehicle.

$$X_{i,j,k} \in \{0,1\}, \qquad \forall (i,j) \in A, k \in K \tag{14}$$

$$F_{i,j,k} \geq 0, \qquad \forall (i,j) \in A, k \in K \tag{15}$$

$$e_i \geq 0, \qquad \forall i \in P \cup D \tag{16}$$

$$l_i \geq 0, \qquad \forall i \in P \cup D \tag{17}$$

$$S_{i,k} \geq 0, \qquad \forall i \in D, k \in K \tag{18}$$

$$Y_{i,k} \geq 0, \qquad \forall i \in V \backslash \{2n+1\}, k \in K \tag{19}$$

$$U_{i,j,k} > 0, \qquad \forall (i,j) \in A, k \in K \tag{20}$$

$$W_{i,j,k} > 0, \qquad \forall (i,j) \in A, k \in K. \tag{21}$$

Constraints (14) to (21) represent the restrictions imposed on the decision variables.

4.2. A linear approximation for the mixed integer nonlinear programming formulation with continuous piecewise linear functions

Solving the above introduced model is complicated as it is a nonlinear model for two reasons: (*i*) the objective function (1) of the model comprises nonlinear parts due to the multiplication and division of the decision variables, X_{ij}, U_{ij} and W_{ij} (Bektaş and Laporte, 2011), and (*ii*) constraints (12) to (13) of the model are nonlinear due to the multiplication and division of the decision variables, X_{ij}, U_{ij}, W_{ij} and Y_i (Cordeau et al., 2007). Accordingly, we suggest here a linear approximation for the mixed integer nonlinear programming formulation using continuous piecewise linear functions.

In addition to the introduced notation in Table 2, Table 3 presents the remaining notations required for the linearized model.

To linearize the objective function, parts (1.i) and (1.ii) are replaced with the following formulations (1.a) and (1.b):

Table 3: Additional parameters and decision variables required for the linearized model

Symbol	Description
R	set of speed intervals (linear lines) for approximating fuel consumption cost and travel time in urban section,
H	set of speed intervals (linear lines) for approximating fuel consumption cost and travel time in non-urban section,
$\pi'_{l,k}$	slope of the linear line $l \in R \cup H$ for emission estimation of vehicle $k \in K$,
$\Omega'_{l,k}$	y-intercept of the linear line $l \in R \cup H$ for emission estimation of vehicle $k \in K$,
π_l	slope of the linear line $l \in R \cup H$ for travel time estimation,
Ω_l	y-intercept of the linear line $l \in R \cup H$ for travel time estimation,
p^l	the lowest speed of the speed interval $l \in R \cup H$, (m/s),
M	a sufficiently large number,
$V^l_{i,j,k}$	average vehicle speed of vehicle $k \in K$ between node i and j, $(i,j) \in A$, for each speed interval $l \in R \cup H$, (m/s),
$Z^l_{i,j,k}$	binary variable equal to 1 if vehicle $k \in K$ travels at speed interval $l \in R \cup H$ on arc $(i,j) \in A$, and 0 otherwise.

$$
\begin{aligned}
&\sum_{k\in K}\sum_{(i,j)\in A}\left(\sum_{r\in R}(\pi'_{r,k}V^r_{i,j,k} + \Omega'_{r,k}Z^r_{i,j,k})d'_{i,j}\right)\text{price} + \sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[\gamma s\left(\mu_k X_{i,j,k} + F_{i,j,k}\right)d'_{i,j}\right]\text{price} && (1.a)\\
&+\sum_{k\in K}\sum_{(i,j)\in A}\left(\sum_{h\in H}(\pi'_{h,k}V^h_{i,j,k} + \Omega'_{h,k}Z^h_{i,j,k})d''_{i,j}\right)\text{price} + \sum_{k\in K}\sum_{(i,j)\in A}\lambda\left[\gamma s\left(\mu_k X_{i,j,k} + F_{i,j,k}\right)d''_{i,j}\right]\text{price}. && (1.b)
\end{aligned}
\tag{22}
$$

Note that in the first components of the equations (1.a) and (1.b), the slope intercept form of a linear equation has been used to define the piecewise linear lines[1]. The resulting objective function of the mixed integer linear programming formulation comprises four parts: (1.a), (1.b), (1.iii) and (1.iv).

Nonlinear constraints (12) to (13) are replaced with the following linear ones, respectively:

$$
Y_{i,k} - Y_{j,k} + t_i + \left[d'_{i,j}\left(\sum_{r\in R}\pi_r V^r_{i,j,k} + \Omega_r Z^r_{i,j,k}\right)\right] + \left[d''_{i,j}\left(\sum_{h\in H}\pi_h V^h_{i,j,k} + \Omega_h Z^h_{i,j,k}\right)\right] \le M(1 - X_{i,j,k}),
$$

$$
\forall i,j \in V\backslash\{2n+1\} : (i,j) \in A, k \in K \tag{23}
$$

$$
Y_{j,k} + t_j - S_{j,k} + \left[d'_{j,2n+1}\left(\sum_{r\in R}\pi_r V^r_{j,2n+1,k} + \Omega_r Z^r_{j,2n+1,k}\right)\right] + \left[d''_{j,2n+1}\left(\sum_{h\in H}\pi_h V^h_{j,2n+1,k} + \Omega_h Z^h_{j,2n+1,k}\right)\right] \le M(1 - X_{j,2n+1,k}),
$$

$$
\forall j \in D, k \in K. \tag{24}
$$

In addition to the big M method, similar to the application for the objective function, in constraints (23)

[1] The process of piecewise linearisation can be explained as follows: (i) Select a number of points on the function arbitrarily and determine (x,y) coordinates of the points. (ii) For each pair of successive points, find the function of the linear line that passes through these points. An interested reader to have more information on the piecewise linear approximation can be referred to the studies conducted by Al-Salem et al. (2016); Diabat and Theodorou (2015); Kilic (2011).

and (24) the slope intercept of a linear equation has been used for travel time estimation.

Constraints (25) to (29) are used for the linear approximation of the fuel consumption cost and travel time.

$$V^l_{i,j,k} \leq Z^l_{i,j,k} M, \qquad \forall (i,j) \in A, k \in K, l \in R \cup H \tag{25}$$

$$V^l_{i,j,k} \geq p^l Z^l_{i,j,k}, \qquad \forall (i,j) \in A, k \in K, l \in R \cup H \tag{26}$$

$$V^l_{i,j,k} < p^{l+1} + (1 - Z^l_{i,j,k}) M, \qquad \forall (i,j) \in A, k \in K, l \in R \cup H \tag{27}$$

$$\sum_{r \in R} Z^r_{i,j,k} = X_{i,j,k}, \qquad \forall (i,j) \in A, k \in K \tag{28}$$

$$\sum_{h \in H} Z^h_{i,j,k} = X_{i,j,k}, \qquad \forall (i,j) \in A, k \in K. \tag{29}$$

Constraints (30) to (31) represent the restrictions imposed on the new decision variables.

$$V^l_{i,j,k} \geq 0, \qquad \forall (i,j) \in A, k \in K, l \in R \cup H \tag{30}$$

$$Z^l_{i,j,k} \in \{0,1\}, \qquad \forall (i,j) \in A, k \in K, l \in R \cup H. \tag{31}$$

The resulting mixed integer linear programming formulation for the defined problem is as follows. The objective function comprises (1.a), (1.b), (1.iii) and (1.iv), and the constraints are: (2)–(11), (14)–(19), and (23)–(31).

5. Numerical experimentation

This section presents computational analyses of the implementation of the linearized model on the distribution operations of a hypothetical company operating in the Netherlands. The aim of the analysis is to show the applicability and potential benefits of the proposed decision support model for the green one-to-one PDP with road segmentation. We first describe the case and the data used, then present the results.

5.1. A case description and data characteristics

The underlying transportation network includes one depot, five pickup and five corresponding delivery locations as presented in Figure 2. The delivery amounts and pickup-delivery pairs are as follows: 3250 kg

(Amsterdam to Enschede), 1500 kg (Groningen to Eindhoven), 1500 kg (Hertogenbosch to Zwolle), 2750 kg (Emmen to Rotterdam), 2500 kg (Apeldoorn to Nijmegen).

Figure 2: Representation of the logistics network

Table 4 presents time windows for the pickup and delivery locations. Service times are assumed to be 500 s for all customer nodes. Time window violation cost is assumed as 0.01 €/s for each pickup and delivery location.

Table 4: Time windows for the pickup and delivery locations, in seconds

Location	Time window	
	Lower bound	Upper bound
Amsterdam	1000	3000
Groningen	2000	6000
Hertogenbosch	3000	9000
Emmen	4000	12000
Apeldoorn	5000	15000
Enschede	3000	18000
Eindhoven	4000	21000
Zwolle	5000	24000
Rotterdam	6000	27000
Nijmegen	7000	30000

Distances between nodes considering urban and non-urban sections (see Table A.1 in the appendix) are calculated using Google Maps[2]. Speed intervals (linear lines) to approximate fuel consumption cost and travel time in urban sections are as follows: (10-15), (15-20), (20-25) and (25-30) km/h. For non-urban sections, speed intervals are (90-95), (95-100), (100-105), (105-110), (110-115) and (115-120) km/h.

The parameters used to calculate the total fuel consumption cost are taken from Demir et al. (2012) and

[2]http://maps.google.com.tr/,Onlineaccessed:September2016

Demir and Van Woensel (2013), and are given in Table 5. As presented in the table, we assume that two heterogenous vehicles are used for the delivery operations. A fuel conversion factor of 2.63 kg/l has been used to estimate CO_2 emissions from transportation operations (Defra, 2007). The data used in the base setting are presented in Table A.2.

Table 5: Setting of vehicle and emission parameters

Notation*	Description	Vehicles 1-2
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/liter)	737
k_k	Engine friction factor (kJ/rev/liter)	0.2 - 0.25
N_k	Engine speed (rev/s)	33 - 51
V_k	Engine displacement (liter)	5 - 7
ρ	Air density (kg/m^3)	1.2041
A_k	Frontal surface area (m^2)	3.912 - 5.88
μ_k	Curb-weight (kg)	6350 - 11793
Q_k	Vehicle capacities (kg)	3650 - 7000
g	Gravitational constant (m/s^2)	9.81
ϕ	Road angle	0
C_d	Coefficient of aerodynamic drag	0.7
C_r	Coefficient of rolling resistance	0.01
ε	Vehicle drive train efficiency	0.4
ϖ	Efficiency parameter for diesel engines	0.9
l	Fuel price per liter (€)	1.5
r	Driver wage (€/s)	0.003

Source: Demir et al. (2012) and Demir and Van Woensel (2013)
* See section 3 for the description of the notation.

5.2. Computational analyses

Before we proceed, we note that the proposed linearized model respects road categorization, and the arcs between nodes in our above introduced case have urban and non-urban segments with varying distances. In our numerical experimentation, we analyze four delivery plans for the studied case which are named as delivery plan A, delivery plan B, delivery plan B1 and delivery plan B2 to assess the potential benefits of accounting for road categorization in the proposed decision support model.

The delivery plans A and B have been obtained from the proposed model by means of using two different parameter settings. In the first parameter setting, urban and non-urban segments of each arc and the corresponding speed options have been respected to allow our model to provide a delivery plan (i.e., plan A) that takes road segments into account. Whereas in the second parameter setting, urban segments of each arc and therefore the urban speed limits have been ignored and it is assumed that the whole travel in each arc is made only in non-urban roads. Accordingly, the model fed with the second parameter setting provides a delivery plan (i.e., plan B) that ignores road segments. This plan, therefore, leads to have vehicles that retain their speeds in urban parts as well, although the vehicle speed is above the maximum urban speed limit.

Due to the ignorance of urban road segments, the delivery plan B cannot be directly implemented in practice. As one would appreciate, urban roads often have maximum speed limits and traffic congestion does not allow vehicles to have the same travel speeds in urban roads as in non-urban ones. This has motivated us to derive the delivery plans B1 and B2 from the delivery plan B. These derived plans use the same routes with the delivery plan B and basically enable to show the performance of the implementation of the proposed routes that comprise arcs with urban and non-urban road segments.

The delivery plan B1, which is derived from the delivery plan B, sticks to the suggested vehicle speeds in non-urban segments; however, it respects to the existing maximum speed limit of urban parts. The best urban speed option in terms of both fuel consumption and travel time, which is the maximum speed level for the urban parts, has been assigned as vehicle speed for urban travels.

The delivery plan B2, which is derived from the delivery plan B, also respects to the speed limits in urban parts and uses the same urban speed with the delivery plan B1. As distinct from the delivery plan B1, the delivery plan B2 aims to ensure the same travel times between nodes with the delivery plan B as much as possible. To reach the same travel times, vehicle speeds in non-urban parts are increased to compensate the time loss in urban area. Note that the same travel times with the delivery plan B in each arc cannot always be obtained due to the maximum non-urban speed limit. Since vehicles are not allowed to travel at speed that is more than the maximum level in non-urban parts, the realized travel times in practice for the delivery plan B2 are sometimes higher than the ones given for the delivery plan B.

The proposed model used to obtain the above mentioned delivery plans has been developed and solved with the ILOG-OPL development studio and CPLEX 12.6 optimization package. The resulting integrated model for our case study has 2142 continuous and 2090 binary variables, and 6559 constraints. Optimal solutions are acquired on a computer of Pentium(R) i7 2.4GHz CPU with 8GB memory. According to our experimentation, it takes on average nearly three minutes to get optimal solutions.

In our experimentation, we focus on several logistical KPIs to make performance comparisons among the delivery plans. These selected logistical KPIs have been used in other studies (e.g., Soysal (2016); Soysal and Çimen (2017); Çimen and Soysal (2017)) as well and are as follows: (*i*) total emissions, (*ii*) total driving time, (*iii*) total fuel consumption cost, (*iv*) total wage cost, (*v*) total penalty cost due to violation of time window restrictions, and (*vi*) total cost.

5.2.1. An optimal solution for the case study

This section provides a solution for the case study. Table 7 gives detailed presentation of the delivery plans including information on the used vehicle routes, travel distance and time, vehicle load, fuel consumption in urban and non-urban parts and time window violations. The main insights that are observed from the presented delivery plans are briefly discussed as follows.

First, accounting for road categorization has an impact on the resulting vehicle routes as shown from the employed routes in the delivery plan A and the others. For example, according to the delivery plan A, vehicle type one follows the route of 0-1-6-3-8-11, whereas this changes to 0-3-8-4-9-11 in the delivery plan B and accordingly in the derived ones B1 and B2.

Second, results on the delivery plans B and derived plans B1 and B2 show that when the vehicle routes suggested by the delivery plan B are implemented, the amount of realized fuel consumption and travel times differ from the ones calculated for the delivery plan B. For example, the delivery plan B suggests vehicle type two to first visit pickup location one from the depot. When the fact that a part of this travel is made in urban road segment of this arc (0 to 1) is considered, the corresponding total fuel consumption amount is increased from 18.20 to 18.52 liters and the travel time is increased from 1307.96 to 2369.81 seconds. The increase in travel times in the delivery plans B1 and B2 results in higher penalty costs due to more time window violations than the ones which are expected in the delivery plan B.

Third, note that the derived delivery plan B2 aims to ensure the same travel times with the delivery plan B in each arc by increasing vehicle speeds in non-urban area. For example, for the arc 4 to 9, to ensure the same travel time (8792 s) with the delivery plan B, the speed of vehicle type one has increased from 25 to 26.70 m/s in the delivery plan B2. However, having the same travel time could not be achieved always as can be observed from the arc 5 to 10. The corresponding travel time in the delivery plan B is 2245.01 s. In the delivery plan B2, the vehicle speed has increased from 30.56 to the maximum urban speed 33.33 meters/seconds in this arc. However, the resulting travel time in this arc is still 3047.80, which shows that even such an increase in non-urban vehicle speed is not sufficient to preserve the same travel time (2245.01) with the one calculated in the delivery plan B.

Table 6 presents the summary results for each delivery plan. Note that the delivery plan B cannot be directly implemented in practice as it ignores the existing road categorization.

The results show that the delivery plan A that accounts for the existing road segmentation outperforms the two different implementations (plan B1 and B2) of the delivery plan B in terms of total cost. The total cost gaps are 4.7% between the delivery plan A and B1 and 5.2% between the delivery plan A and B2.

It has been observed that when the delivery plan B has been implemented in practice through the delivery plans B1 and B2, all of the cost components which are fuel consumption, wage and penalty costs show an increase. The reason behind such increases in the cost components is the fact that lower vehicle travel speeds

Table 6: Summary results for each delivery plan

KPIs	**Plan A**	**Plan B**	**Plan B1**	**Plan B2**
Total emissions(kg)	1086.00	1032.12	1041.39	1101.10
Emissions from Urban Area(kg)	102.43	0.00	101.87	101.87
Emissions from Non-urban Area(kg)	983.58	1032.12	939.52	999.23
Total driving time(s)	56768.28	49469.24	58335.72	54631.10
Total fuel consumption cost(€)	619.39	588.66	593.95	628.01
Total wage cost(€)	170.30	148.41	175.01	163.89
Total penalty cost(€)	82.93	23.12	144.52	126.27
Early penalty(€)	0.00	0.00	0.00	0.00
Late penalty(€)	82.93	23.12	144.52	126.27
Total cost(€)	872.62	760.19	913.48	918.17

Table 7: Representation of the resulting routes in each delivery plan

	Arc	UD(m)	US(m\s)	ND(m)	NS(m\s)	VL(kg)	VT	FCU(liter)	FCN(liter)	TFC(liter)	TT(s)	ST(s)	Y_j(s)	Window(s)		Early(s)	Late(s)
Plan A	0-1	11800	8.33	31800	31.95	0	1	2.19	7.29	9.48	2411.28	500	2911.28	1000	3000		
	1-6	9000	8.33	153000	31.95	3250	1	1.91	39.27	41.18	5869.30	500	9280.58	3000	18000		
	6-3	6900	8.33	153000	31.95	0	1	1.28	35.09	36.37	5617.33	500	15397.91	3000	9000		6397.91
	3-8	6700	8.33	124000	25.00	1500	1	1.33	24.17	25.50	5763.91	500	21661.81	5000	24000		
	8-11	3300	8.33	86200	25.00	0	1	0.61	15.72	16.33	3843.95	500	26005.77				
	0-2	9500	8.33	178000	33.33	0	2	4.22	74.32	78.54	6479.71	500	6979.71	2000	6000		979.71
	2-4	8900	8.33	51600	33.33	1500	2	4.06	22.20	26.26	2615.83	500	10095.54	4000	12000		
	4-5	10700	8.33	102000	33.33	4250	2	5.13	46.23	51.36	4343.76	500	14939.31	3000	18000		
	5-10	11000	8.33	57600	33.33	6750	2	5.51	27.32	32.83	3047.80	500	18487.10	7000	30000		
	10-7	10500	8.33	55600	33.33	4250	2	5.04	25.20	30.24	2927.81	500	21914.91	4000	21000		914.91
	7-9	7000	8.33	103000	27.51	2750	2	3.27	39.44	42.71	4583.74	500	26998.65	6000	27000		
	9-11	9900	8.33	51900	25.00	0	2	4.40	17.74	22.14	3263.86	500	30762.51				
Plan B	0-1	0	-	43600	33.33	0	2	0.00	18.20	18.20	1307.96	500	1807.96	1000	3000		
	1-2	0	-	183400	33.33	3250	2	0.00	81.58	81.58	5501.84	500	7809.80	2000	6000		1809.80
	2-6	0	-	148700	33.33	4750	2	0.00	68.02	68.02	4460.87	500	12770.67	3000	18000		
	6-5	0	-	74400	33.33	1500	2	0.00	32.00	32.00	2231.94	500	15502.61	5000	15000		502.61
	5-10	0	-	68600	30.56	4000	2	0.00	28.88	28.88	2245.01	500	18247.62	7000	30000		
	10-7	0	-	66100	29.35	1500	2	0.00	25.67	25.67	2251.83	500	20999.45	4000	21000		
	7-11	0	-	92700	25.00	0	2	0.00	31.69	31.69	3708.00	500	25207.45				
	0-3	0	-	54800	25.00	0	1	0.00	9.99	9.99	2192.00	500	3000.00	3000	9000		
	3-8	0	-	130700	26.13	1500	1	0.00	26.31	26.31	5001.79	500	8501.79	5000	24000		
	8-4	0	-	74900	25.00	0	1	0.00	13.66	13.66	2996.00	500	11997.79	4000	12000		
	4-9	0	-	219800	25.00	2750	1	0.00	45.16	45.16	8792.00	500	21289.79	6000	27000		
	9-11	0	-	61800	25.00	0	1	0.00	11.27	11.27	2472.00	500	24261.79				
Plan B1	0-1	11800	8.33	31800	33.33	0	2	5.24	13.28	18.52	2369.81	500	2869.81	1000	3000		
	1-2	12400	8.33	171000	33.33	3250	2	5.85	76.07	81.91	6617.68	500	9987.49	2000	6000		3987.49
	2-6	4700	8.33	144000	33.33	4750	2	2.27	65.87	68.15	4883.81	500	15371.30	3000	18000		
	6-5	8100	8.33	66300	33.33	1500	2	3.70	28.52	32.22	2960.83	500	18832.13	5000	15000		3832.13
	5-10	11000	8.33	57600	30.56	4000	2	5.25	24.25	29.50	3204.87	500	22537.00	7000	30000		
	10-7	10500	8.33	55600	29.35	1500	2	4.80	21.59	26.39	3153.98	500	26190.98	4000	21000		5190.98
	7-11	11200	8.33	81500	25.00	0	2	4.97	27.86	32.83	4603.84	500	31294.82				
	0-3	5400	8.33	49400	25.00	0	1	1.00	9.01	10.01	2623.92	500	3431.92	3000	9000		
	3-8	6700	8.33	124000	26.13	1500	1	1.33	24.97	26.29	5549.29	500	9481.21	5000	24000		
	8-4	5800	8.33	69100	25.00	0	1	1.07	12.60	13.67	3459.92	500	13441.13	4000	12000		1441.13
	4-9	6800	8.33	213000	25.00	2750	1	1.42	43.76	45.18	9335.91	500	23277.04	6000	27000		
	9-11	9900	8.33	51900	25.00	0	1	1.83	9.46	11.30	3263.86	500	27040.90				
Plan B2	0-1	11800	8.33	31800	33.33	0	2	5.24	13.28	18.52	2369.81	500	2869.81	1000	3000		
	1-2	12400	8.33	171000	33.33	3250	2	5.85	76.07	81.91	6617.68	500	9987.49	2000	6000		3987.49
	2-6	4700	8.33	144000	33.33	4750	2	2.27	65.87	68.15	4883.81	500	15371.30	3000	18000		
	6-5	8100	8.33	66300	33.33	1500	2	3.70	28.52	32.22	2960.83	500	18832.13	5000	15000		3832.13
	5-10	11000	8.33	57600	33.33	4000	2	5.25	25.99	31.24	3047.80	500	22379.92	7000	30000		
	10-7	10500	8.33	55600	33.33	1500	2	4.80	23.92	28.71	2927.81	500	25807.73	4000	21000		4807.73
	7-11	11200	8.33	81500	33.33	0	2	4.97	34.03	39.00	3788.77	500	30096.50				
	0-3	5400	8.33	49400	31.99	0	1	1.00	11.35	12.35	2192.00	500	3000.00	3000	9000		
	3-8	6700	8.33	124000	29.54	1500	1	1.33	27.73	29.06	5001.79	500	8501.79	5000	24000		
	8-4	5800	8.33	69100	30.04	0	1	1.07	14.84	15.91	2996.00	500	11997.79	4000	12000		
	4-9	6800	8.33	213000	26.70	2750	1	1.42	45.86	47.27	8792.00	500	21289.79	6000	27000		
	9-11	9900	8.33	51900	33.33	0	1	1.83	12.50	14.33	2744.82	500	24534.60				

UD: Distance of urban segment, US: Speed in urban segment, ND: Distance of non-urban segment, NS: Speed in non-urban segment, VL: Vehicle load, VT: Vehicle type, FCU: Fuel consumption urban, FCN: Fuel consumption non-urban, TFC: Total fuel consumption, TT: Travel time, ST: Service time, Y_j: Service start time at node j

Nodes 0 and 11: Utrecht, 1: Amsterdam, 2: Groningen, 3: Hertogenbosch, 4: Emmen, 5: Apeldoorn, 6: Enschede, 7: Eindhoven, 8: Zwolle, 9: Rotterdam and 10: Nijmegen.

in urban road segments lead to higher fuel consumption, driving time and time window violations than the ones which are expected in the delivery plan B.

5.2.2. Effects of changing key modelling parameters

This section aims to present the variations in the resulting routes and the defined logistical KPIs when the values of key modelling parameters have been changed. Accordingly, eight more scenarios are defined as follows.

- The penalty cost of time violation at pickup and delivery locations has been changed from 0.01 to 0.005 (Low penalty scenario) and to 0.02 €/s (High penalty scenario).
- The time windows for pickup and delivery locations have been relaxed 25% (Relaxed window scenario) and tightened 25% (Tight window scenario) from both sides.
- The delivery amounts have been changed as follows: Amsterdam - 1350 kg, Groningen - 3400 kg, Hertogenbosch - 4250 kg, Emmen - 750 kg and Apeldoorn - 3600 kg (Demand 1 scenario), and Amsterdam - 500 kg, Groningen - 4800 kg, Hertogenbosch - 1400 kg, Emmen - 1650 kg and Apeldoorn - 1200 kg (Demand 2 scenario).
- The pickup-delivery pairs have been changed as follows: Enschede to Hertogenbosch, Rotterdam to Eindhoven, Emmen to Nijmegen, Groningen to Amsterdam and Zwolle to Apeldoorn (Pair set 1 scenario), and Nijmegen to Eindhoven, Emmen to Hertogenbosch, Amsterdam to Zwolle, Rotterdam to Enschede and Apeldoorn to Groningen (Pair set 2 scenario).

Table 8 presents the suggested vehicle routes for each plan under different scenarios and Table 9 presents the summary results for the scenario analyses. The following key messages obtained from the conducted analyses.

In all scenarios, except the Pair set 1 scenario, taking road categorization into account alters the resulting vehicle routes as shown in Table 8 (i.e., the suggested routes of plans A and B are different from each other). In the Pair set 1 scenario, the delivery plan A still outperforms the derived delivery plans B1 and B2 in terms of total cost (see Table 9), though the same routes have been used in these plans. The differences between the costs of plan A and plan B1, and plan A and plan B2, come from the fact that the suggested vehicle speeds in the delivery plan A are not the same as the ones used in delivery plans B1 and B2. Moreover, in all of the remaining scenarios the delivery plans that consider road categorization (plans A) show the best

Table 8: Suggested vehicle routes for each plan under different scenarios

Scenarios	Delivery plans	Vehicle types 1	Vehicle types 2
Base setting	Plan A	Utr-Ams-Ens-Her-Zwo-Utr	Utr-Gro-Emm-Ape-Nij-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Her-Zwo-Emm-Rot-Utr	Utr-Ams-Gro-Ens-Ape-Nij-Ein-Utr
Low penalty	Plan A	Utr-Ams-Ens-Ape-Nij-Her-Zwo-Utr	Utr-Gro-Emm-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Ams-Ens-Her-Zwo-Utr	Utr-Gro-Emm-Ape-Nij-Ein-Rot-Utr
High penalty	Plan A	Utr-Ams-Ens-Her-Zwo-Utr	Utr-Gro-Emm-Ape-Nij-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Her-Zwo-Emm-Rot-Utr	Utr-Ams-Gro-Ens-Ape-Nij-Ein-Utr
Relaxed window	Plan A	Utr-Ams-Ens-Ape-Nij-Utr	Utr-Her-Gro-Emm-Zwo-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Her-Zwo-Emm-Rot-Utr	Utr-Ams-Gro-Ens-Ape-Nij-Ein-Utr
Tight window	Plan A	Utr-Ams-Ens-Emm-Rot-Utr	Utr-Her-Ape-Zwo-Gro-Nij-Ein-Utr
	Plan B, B1, B2	Utr-Ams-Ens-Ape-Nij-Her-Zwo-Utr	Utr-Gro-Emm-Ein-Rot-Utr
Demand 1	Plan A	Utr-Ams-Ens-Ape-Nij-Utr	Utr-Her-Zwo-Emm-Gro-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Ams-Ens-Ape-Nij-Utr	Utr-Her-Zwo-Gro-Emm-Ein-Rot-Utr
Demand 2	Plan A	Utr-Ams-Her-Ape-Ens-Zwo-Nij-Utr	Utr-Gro-Emm-Ein-Rot-Utr
	Plan B, B1, B2	Utr-Ams-Her-Ape-Zwo-Ens-Nij-Utr	Utr-Gro-Emm-Ein-Rot-Utr
Pair set 1	Plan A	Utr-Ens-Her-Rot-Ein-Utr	Utr-Gro-Emm-Zwo-Ape-Ams-Nij-Utr
	Plan B, B1, B2	Utr-Ens-Her-Rot-Ein-Utr	Utr-Gro-Emm-Zwo-Ape-Ams-Nij-Utr
Pair set 2	Plan A	Utr-Ape-Gro-Emm-Her-Nij-Ein-Utr	Utr-Ams-Rot-Ens-Zwo-Utr
	Plan B, B1, B2	Utr-Ape-Gro-Emm-Her-Nij-Ein-Utr	Utr-Ams-Rot-Zwo-Ens-Utr

Nodes 0 and 11: Utrecht, 1: Amsterdam, 2: Groningen, 3: Hertogenbosch, 4: Emmen, 5: Apeldoorn, 6: Enschede, 7: Eindhoven, 8: Zwolle, 9: Rotterdam and 10: Nijmegen.

cost performance (see Table 9). These results demonstrate the benefit of accounting for road categorization in the proposed decision support model for the green one-to-one PDP.

The scenario analyses on the penalty cost show that compared to the base setting, the penalty cost decrease leads to a change in vehicle routes, whereas its increase has not affected the resulting routes. Another result is that the benefit of accounting for road categorization has decreased in the low penalty scenario and increased in the high penalty scenario.

The resulting routes from the delivery plan A that accounts for road categorization have been affected from the time window tightness. The resulting routes from the delivery plan B, and derived plans B1 and B2 that do not consider road categorization are changed in the tight window scenario, but remained the same in the relaxed window scenario. The time window tightness, however, has affected the logistical KPIs in varying degrees. The benefit of accounting for road categorization has decreased when the time windows become more tight compared to the ones in the base setting. For the relaxed window scenario, the change in the benefit of accounting for road categorization compared to the base setting varies depending on whether the delivery plan B1 or B2 is implemented.

It has been observed that the change in the delivery amounts or in the the pickup-delivery pairs leads

Table 9: Summary results for the scenario analyses

		UE(kg)	NE(kg)	TE(kg)	TD(s)	TF(€)	TW(€)	Penalty(€) Early	Late	Total Cost(€)	Gap
Base Setting	Plan A	102.43	983.58	1086.00	56768.28	619.39	170.30	0.00	82.93	872.62	
	Plan B	0.00	1032.12	1032.12	49469.24	588.66	148.41	0.00	23.12	760.19	-12.9%
	Plan B1	101.87	939.52	1041.39	58335.72	593.95	175.01	0.00	144.52	913.48	4.7%
	Plan B2	101.87	999.23	1101.10	54631.10	628.01	163.89	0.00	126.27	918.17	5.2%
LP	Plan A	86.44	921.39	1007.83	59501.43	574.81	178.50	0.00	63.52	816.83	
	Plan B	0.00	967.14	967.14	53337.17	551.60	160.01	0.00	32.93	744.54	-8.9%
	Plan B1	102.43	880.86	983.28	61940.55	560.81	185.82	0.00	87.48	834.11	2.1%
	Plan B2	102.43	1004.82	1107.25	55325.51	631.51	165.98	0.00	41.76	839.25	2.7%
HP	Plan A	102.43	993.77	1096.20	56330.70	625.21	168.99	0.00	157.04	951.24	
	Plan B	0.00	1032.11	1032.11	49471.57	588.66	148.41	0.00	46.25	783.33	-17.7%
	Plan B1	101.87	939.48	1041.35	58034.10	593.93	174.10	0.00	282.96	1050.99	10.5%
	Plan B2	101.87	999.92	1101.79	54633.57	628.40	163.90	0.00	252.57	1044.87	9.8%
RW	Plan A	88.72	910.51	999.23	59101.05	569.90	177.30	0.00	39.55	786.75	
	Plan B	0.00	953.40	953.40	53131.84	543.76	159.40	0.00	9.29	712.45	-9.4%
	Plan B1	101.87	867.64	969.51	61650.41	552.95	184.95	0.00	91.26	829.16	5.4%
	Plan B2	101.87	995.83	1097.70	54552.32	626.07	163.66	0.00	25.70	815.42	3.6%
TW	Plan A	96.05	1005.94	1101.98	56060.67	628.51	168.18	9.85	258.54	1065.08	
	Plan B	0.00	1093.32	1093.32	46245.48	623.57	138.74	0.00	101.73	864.03	-18.9%
	Plan B1	86.44	1005.80	1092.24	55521.48	622.95	166.56	0.00	293.16	1082.67	1.7%
	Plan B2	86.44	1039.88	1126.32	53872.21	642.39	161.62	0.00	282.63	1086.64	2.0%
D1	Plan A	89.45	975.18	1064.62	55297.83	607.20	165.89	3.70	106.23	883.03	
	Plan B	0.00	1011.96	1011.96	48921.36	577.17	146.76	8.56	47.38	779.87	-11.7%
	Plan B1	90.27	930.81	1021.08	57488.93	582.37	172.47	3.70	144.81	903.35	2.3%
	Plan B2	90.27	1015.24	1105.51	52381.25	630.52	157.14	3.70	117.98	909.34	3.0%
D2	Plan A	87.44	867.98	955.42	61016.36	544.91	183.05	0.00	12.12	740.08	
	Plan B	0.00	929.59	929.59	53119.15	530.18	159.36	0.00	6.36	695.90	-6.0%
	Plan B1	86.64	854.83	941.47	61514.81	536.96	184.54	0.00	34.89	756.40	2.2%
	Plan B2	86.64	965.28	1051.93	54648.85	599.96	163.95	0.00	9.80	773.70	4.5%
S1	Plan A	91.83	958.98	1050.80	56670.11	599.32	170.01	0.00	195.82	965.15	
	Plan B	0.00	1018.79	1018.79	49283.05	581.06	147.85	0.00	149.81	878.72	-9.0%
	Plan B1	91.83	936.59	1028.42	57622.74	586.55	172.87	0.00	213.26	972.68	0.8%
	Plan B2	91.83	1033.44	1125.27	52477.31	641.79	157.43	0.00	193.72	992.94	2.9%
S2	Plan A	68.36	821.35	889.70	54641.88	507.43	163.93	17.31	182.08	870.75	
	Plan B	0.00	883.41	883.41	47170.26	503.85	141.51	24.96	86.72	757.04	-13.1%
	Plan B1	68.47	815.73	884.20	55341.02	504.30	166.02	17.31	188.03	875.66	0.6%
	Plan B2	68.47	859.67	928.14	52610.34	529.36	157.83	17.31	182.55	887.05	1.9%

UE: Emissions from urban area, NE: Emissions from non-urban area, TE: Total emissions, TD: Total driving time,
TF: Total fuel consumption cost, TW: Total wage cost,
LP: Low penalty scenario, HP: High penalty scenario, RW: Relaxed window scenario, TW: Tight window scenario,
D1: Demand 1 scenario, D2: Demand 2 scenario, S1: Pair set 1 scenario, S2: Pair set 2 scenario

to a change in resulting vehicle routes. Here, the main message from these four scenarios (Demand 1, 2 and Pair set 1, 2 scenarios) is that accounting for road categorization still provides a cost advantage, but its benefit has decreased compared to the base setting.

5.2.3. Benefit of accounting for explicit fuel consumption estimation

We would like to note that the objective function of the linearized model comprises fuel consumption cost from transportation operations in urban and non-urban sections, driver cost and penalty cost for breaking soft time windows. In this section, the objective function is adapted to demonstrate the benefit of accounting for explicit fuel consumption estimation. In particular, fuel consumption cost from transportation operations in urban section (1.a) and fuel consumption cost from transportation operations in non-urban section (1.b) are removed from the objective function, and the formulation is minimized over a new objective function that comprises driver cost (1.iii), and penalty cost for breaking soft time windows (1.iv). The new objective function is traditional in the sense that it takes only total time spent by vehicles and penalty cost into account, and ignores the effects of several parameters on fuel consumption amounts, such as vehicle load, vehicle speed and other vehicle-related characteristics. Figure 3 presents the performance of the new formulation compared to the original one on the base setting with respect to the defined KPIs.

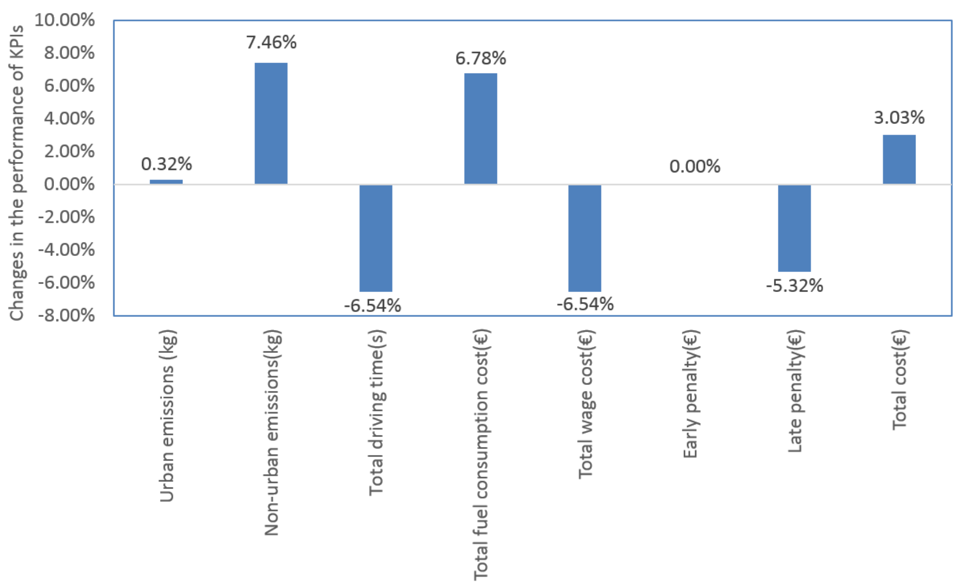

Figure 3: The effects of using a new objective function in the formulation

The results show that the objective function change does not alter the resulting vehicle routes, whereas the KPIs are affected. The use of the new objective enables to reduce total driving time by 6.54% (3714.95 s), total wage cost by 6.54% (€11.14) and total penalty cost by 5.32% (€4.41). However, the ignorance of fuel consumption cost results in an increase of urban emissions by 0.32% (0.33 kg), non-urban emissions by 7.46% (73.33 kg), total fuel consumption cost by 6.78% (€42.01) and total cost by 3.03% (€26.46). Therefore, the extended objective function through explicit fuel consumption estimation enables to provide better delivery plan in terms of total cost.

5.2.4. *Benefit of accounting for vehicle speed as a decision variable*

The proposed model regards travel speed as a decision variable rather than a known parameter, which means that travel speed is not constant and can take any value within given limits. In this section, the model is adapted to demonstrate the benefit of accounting for vehicle speed as a decision variable. In particular, average vehicle speeds in urban and non-urban sections are assumed as known in advance. Those speeds, accordingly, are taken as parameters in the model.

Three scenarios are analysed using the base setting in which corresponding average vehicle speeds in urban and non-urban sections are set as follows: (Scenario *i*) 25 and 90 km/h, (Scenario *ii*) 25 and 105 km/h and (Scenario *iii*) 25 and 120 km/h. Table 10 presents summary results of scenarios where average vehicle speeds are taken as parameters.

Table 10: Summary results of scenarios where average vehicle speeds are regarded as parameters

KPIs	Original plan	Scenario *i*	Scenario *ii*	Scenario *iii*
Total emissions(kg)	1086.00	934.92	1023.48	1154.47
Emissions from Urban Area(kg)	102.43	86.45	86.45	102.43
Emissions from Non-urban Area(kg)	983.58	848.47	937.03	1052.04
Total driving time(s)	56768.28	64726.67	58143.33	53056.67
Total fuel consumption cost(€)	619.39	533.22	583.73	658.44
Total wage cost(€)	170.30	194.18	174.43	159.17
Total penalty cost(€)	82.93	238.68	147.11	78.54
Early penalty(€)	0.00	0.00	0.00	0.00
Late penalty(€)	82.93	238.68	147.11	78.54
Total cost(€)	872.62	966.08	905.27	896.15
Route of vehicle type one	0-1-6-3-8-11	0-1-6-5-10-3-8-11	0-1-6-5-10-3-8-11	0-1-6-3-8-11
Route of vehicle type two	0-2-4-5-10-7-9-11	0-2-4-7-9-11	0-2-4-7-9-11	0-2-4-5-10-7-9-11

The original plan presented in Table 10 is obtained from the proposed model that takes vehicle speed as a decision variable. According to the results, assuming vehicle speeds as known parameters results in worse delivery plans compared to that of the original plan in terms of total cost by 10.7% in Scenario *i*, by 3.7% in Scenario *ii* and by 2.7% in Scenario *iii*. It has been observed that allowing the model to decide vehicle speeds in each arc enables to better manage the trade-offs among fuel consumption, wage and penalty costs. Moreover, vehicle routes are changed in scenarios *i* and *ii* due to fixing the vehicle speeds. In scenario *iii*, the same vehicle routes are obtained with the original plan. Enforcing the highest vehicle speed in the travelled arcs gives opportunity to decrease total wage and penalty costs, but leads to increased fuel consumption amount and therefore cost. See subsection 5.2.5 that travelling with the highest vehicle speed of 120 km/h leads an increase in the amount of fuel consumption per km. In summary, the analyses show that accounting for vehicle speed as a decision variable enables to provide better delivery plan in terms of total cost.

5.2.5. Performance of approximation in amount of fuel consumption estimation

We would like to note that in our computational analyses the linearized model has been employed instead of the nonlinear programming formulation. We have used a linear approximation for the mixed integer nonlinear programming formulation using continuous piecewise linear functions. In particular, nonlinear emission estimation presented in (1.i) and (1.ii) has been linearized as shown in (1.a) and (1.b). In this section, we demonstrate the performance of approximation in amount of fuel consumption estimation. Analyses have been made on a vehicle (Vehicle type one introduced in Table 5) travelling a distance of 100 km with 2000 kg load. For the linearization of fuel consumption, ten piecewise linear lines have been used. Figure 4 presents the fuel consumption amounts with regard to vehicle speeds estimated using nonlinear and linearized functions. According to the results, approximation through piecewise linear functions provides good estimates of fuel consumption amounts.

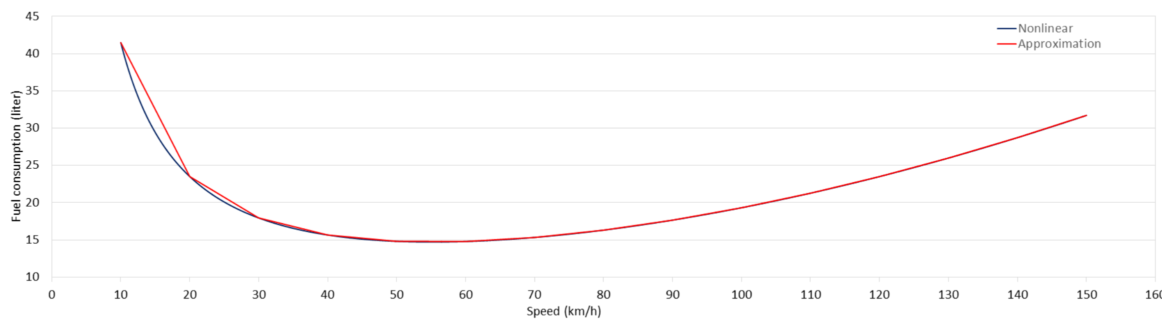

Figure 4: Fuel consumption as a function of speed, liter / 100 km with 2000 kg load of vehicle type one introduced in Table 5.

5.2.6. Trade-offs between environmental and economic objectives

This section aims to reveal compromises between environmental and economic objectives. In order to do so, additional four instances are analyzed by changing the weights of the four components (1.a, 1.b, 1.iii and 1.iv) in the objective function of the linearized model. Here we regard fuel consumption costs (1.a and 1.b) as the environmental components, whereas wage and penalty costs (1.iii and 1.iv) as the economic components of the objective function. In each instance, the following objective functions are used:

Instance 1 0 * (1.a + 1.b) + 1 * (1.iii + 1.iv)

Instance 2 0.25 * (1.a + 1.b) + 0.75 * (1.iii + 1.iv)

Instance 3 0.5 * (1.a + 1.b) + 0.5 * (1.iii + 1.iv)

Instance 4 0.75 * (1.a + 1.b) + 0.25 * (1.iii + 1.iv)

Instance 5 1 * (1.a + 1.b) + 0 * (1.iii + 1.iv)

The base setting data is used for the analyses on these five instances. Figure 5 presents the total emissions and total costs yielded by the solutions of each instance.

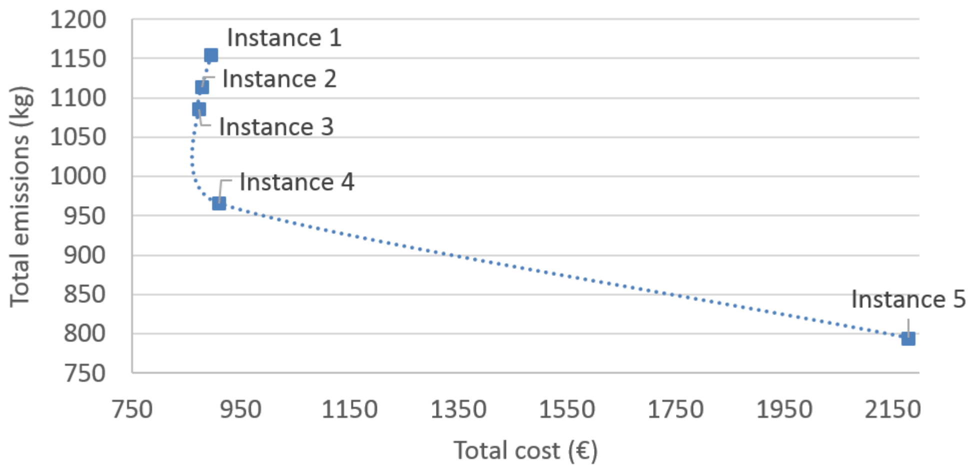

Figure 5: Trade-offs between environmental and economic objectives

The results show the need for compromises between economic and environmental objectives. The decrease of total emissions from 965.77 kg Instance 4 to 794.59 kg (Instance 5) comes at a cost increase from €910.37 to €2179.77 . However, win-win situations between economic and environmental objectives could be also observed. For example, it is possible to reduce both total emissions and total costs simultaneously as can be seen between Instance 2 and Instance 3. In this example, driver and penalty costs increase when their weights in the objective function are decreased. However, the change in fuel costs is relatively higher, which results in lower total cost in Instance 3 (see Table A.3). Such information could be helpful for decision makers while setting sustainability targets that need an evaluation of economic and environmental factors.

6. Conclusions

In this paper, we have modeled and analyzed the green one-to-one PDP to account for explicit fuel consumption, variable vehicle speed and road categorization. To the best of our knowledge, the model is unique in considering the aforementioned aspects for the studied problem. The model manages relevant logistical KPIs of total energy use (which can be translated into emissions), total driving time and total cost comprising fuel consumption, wage and penalty cost due to violation of time window restrictions. The proposed model can be used by decision makers to aid sustainable logistics decision-making process in making transportation decisions.

We have illustrated the added value of the model by making a broad set of experiments on a case study. Our numerical experimentation provides the following important insights. Accounting for explicit fuel consumption, variable vehicle speed and road categorization have a significant impact on logistics decisions and the defined KPIs. Enhancement of the decision support model through the aforementioned aspects enables to provide better delivery plans in terms of total cost in all studied scenarios. The total cost gain is observed to be (*i*) 3.03% by the use of explicit fuel consumption estimation, (*ii*) up to 10.7% by accounting for variable vehicle speed and (*iii*) up to 10.5% by considering road categorization. The results, therefore, demonstrate the benefit of the proposed decision support model for the one-to-one PDP.

One possible extension of the paper is to consider a generic logistics network that has one-to-many distribution structure in which a pickup location has chance to ask delivery to more than a single delivery location. Another possible extension is to develop new solution approaches or apply the existing techniques for solving the presented nonlinear problem formulation.

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Appendix

In this section, we present the distance data used for the proposed model.

Table A.1: Total motorway and urban distances between nodes, in m

Total Motorway Distance											
	1	2	3	4	5	6	7	8	9	10	11
0	31800	178000	49400	156000	58300	-	-	-	-	-	-
1	-	171000	78600	175000	77000	153000	116000	105000	66600	110000	-
2	174000	-	232000	51600	135000	144000	244000	119000	241000	198000	-
3	78900	229000	-	193000	86900	152000	32100	124000	72700	38500	-
4	174000	50100	193000	-	102000	80900	211000	69000	213000	165000	-
5	77200	138000	85600	106000	-	65900	103000	36500	116000	57600	-
6	-	142000	153000	82400	66300	-	170000	72500	192000	125000	135000
7	110000	-	25500	209000	103000	168000	-	140000	103000	54600	81500
8	105000	101000	-	69100	33000	73700	142000	-	144000	96000	86200
9	70500	238000	69000	-	115000	191000	101000	143000	-	109000	51900
10	111000	195000	37900	164000	-	122000	55600	93900	99900	-	79900

Total Urban Distance											
	1	2	3	4	5	6	7	8	9	10	11
0	11800	9500	5400	7700	8500	-	-	-	-	-	-
1	-	12400	8400	11700	12500	9000	8500	7100	7300	13500	-
2	8100	-	5100	8900	8600	4700	9400	2600	4700	9200	-
3	8800	9100	-	11300	10700	8600	6700	6700	8300	10000	-
4	10200	9000	9600	-	10700	17700	11500	4700	6800	11300	-
5	5500	8200	9300	10100	-	8800	11200	5500	7900	11000	-
6	-	4900	6900	17700	8100	-	8800	2000	4100	8600	5300
7	13100	-	11200	12400	11800	9700	-	7800	7000	11100	11200
8	5500	3900	-	5800	6000	2100	6800	-	2100	6600	3300
9	8400	7700	9700	-	7800	4300	9800	2400	-	10700	9900
10	12400	9800	8600	11700	-	9000	10500	7100	17800	-	10200

Nodes 0 and 11: Utrecht, 1: Amsterdam, 2: Groningen, 3: Hertogenbosch, 4: Emmen, 5: Apeldoorn, 6: Enschede, 7: Eindhoven, 8: Zwolle, 9: Rotterdam and 10: Nijmegen.

Table A.2: The data used in the base setting

Data type	**Values**
Logistics network	See Figure 2
Delivery amounts and Pickup-delivery pairs	3250 kg (Amsterdam to Enschede), 1500 kg (Groningen to Eindhoven), 1500 kg (Hertogenbosch to Zwolle), 2750 kg (Emmen to Rotterdam), 2500 kg (Apeldoorn to Nijmegen)
Time windows	See Table 4
Service times	500 s
Time window violation cost	0.01 €/s
Distance matrix	See Table A.1
Speed intervals	(10-15), (15-20), (20-25) and (25-30) km/h (90-95), (95-100), (100-105), (105-110), (110-115) and (115-120) km/h
Number of vehicles	2
Vehicle and emission parameters	See Table 5
Fuel conversion factor	2.63 kg/l

Table A.3: Detailed data for Figure 5: Trade-offs between environmental and economic objectives

	Instance 1	**Instance 2**	**Instance 3**	**Instance 4**	**Instance 5**
Urban fuel cost (1.a)	58,42	58,42	58,42	49,30	42,02
Non-urban fuel cost (1.b)	600,04	576,91	560,99	501,52	411,17
Driver cost (1.iii)	159,16	164,65	170,31	186,32	205,88
Penalty cost (1.iv)	78,52	78,52	82,92	173,23	1520,70
Total cost	**896,14**	**878,50**	**872,64**	**910,37**	**2179,77**
Total emissions	**1154,50**	**1113,95**	**1086,03**	**965,77**	**794,59**

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