The forwarder planning problem in a two-echelon network

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Abstract

This paper is motivated by the case of a forwarder in dealing with inland transportation planning from a seaport, where inbound containers from the sea are filled with pallets, which have different destinations in the landside. Although this forwarder does not have or control any vehicle, he is required to plan the assignment of containers to intermediate depots, where the pallets are unpacked, and, in turn, the assignment of pallets to the vehicles used for the distribution from depots to consignees. We present a mathematical model supporting the forwarder in this two-echelon network to minimize assignment costs, while accounting for a balanced workload among all carriers involved in this distribution scheme. We discuss a tailor-made implementation of the model in a realistic context and present a heuristic method to solve realistic-sized instances. Our computational experiments confirm the viability of this method.

Keywords: *Two-echelon networks, Freight transportation, Forwarder, Combinatorial optimization, Heuristics.*

1 Introduction

Freight transportation is a complex domain, in which the activities of different service operators interact with each other. Much research has been done on optimization methods supporting carriers and terminal operators [5, 9, 11, 13], but limited attention has been devoted to forwarders who do not have or control any vehicle.

A forwarder (or freight forwarder) is a person or firm organizing the shipments of goods toward their destination. It is worth noting that forwarders do not necessarily move goods, but they act as experts in logistics networks. The main role of forwarders is to negotiate the movement and the storage of goods with multiple carriers and warehouses, respectively, in order to select the most suitable transportation opportunities. In addition, they provide additional services, such as the preparation of shipping and export documents, cargo insurance, and filling of insurance claims. For example, forwarders are very common in the field of intermodal freight transportation [8], aircargo services [15] and cash distribution for ATMs [1].

This paper is motivated by the role of a forwarder without vehicles in dealing with the planning of delivery shipments in a seaport, where a fleet of inbound containers from the sea is filled with pallets, which have different destinations in the landside. It is not possible to directly move containers by trucks toward these destinations, because containers cannot enter in many urban streets. Moreover, there exist common policies limiting the impact of large vehicles on city living conditions in terms of congestion, emissions, and pollution [6].

To cope with this situation, freight transportation is performed according to a two-echelon distribution scheme: in the first echelon, containers are moved by trucks to intermediate facilities (or satellites or cross-dock centers), where they are unpacked and the loads are consolidated in different vehicles serving close destinations in the second echelon. A recent review on two-echelon distribution systems has been made by [7].

In the specific case of the distribution from a seaport, satellites are also referred to as dry ports. They are defined as *inland freight terminals directly connected to one or more seaports with high-capacity transport means, where customers can drop and pick up their standardized units as if directly at a seaport* [12]. Generally speaking, dry-ports aim to move in the landside the beneficial effects coming from the use of containers, at bounding congestion at the seaport and decentralizing storage, handling, consolidation and maintenance operations. Moreover, different containers can be assigned to different dry-ports in order to improve the distribution in the second echelon [4]. In this article, we indifferently refer to depots, satellites and dry ports.

In this problem the forwarder needs to quickly remove containers from the seaport and makes two major types of decisions: the assignment of containers to satellites in the first echelon and, in cascade, that of pallets to the vehicles used for the final distribution in the second echelon. The assignment of containers to vehicles is not of interest in the first echelon, as all carriers provide forwarders with the same container transportation fees per unitary distance in the case of full truckload trucking and each container is typically unpacked in a single satellite. The objective of the forwarder is to minimize the overall assignment costs, as well as to guarantee a balanced workload among the vehicles selected in the second echelon. In fact, when few loads are assigned to a vehicle, the carrier may not have sufficient revenues to bear transportation costs and may not be willing to accept the transportation opportunities provided by the forwarder for that vehicle.

This paper focuses on the so-called *day-before* planning, because the definition of distribution activities takes place on the day before, in order to inform all concerned parties on the planned operations timely. Since the forwarder does not have or control any vehicle, there is no interest in the planning of routes to deliver pallets in the second echelon. In addition, the forwarder has little or any information on the routes of vehicles managed by carriers, who often cooperate with several forwarders at the same time. During the planning, the forwarder asks carriers on the available transportation capacity and informs them on the revenue associated with the possible delivery of each pallet from each satellite. Next, the forwarder asks information on the maximum number of containers that can be unpacked at satellites and determine the initial assignment.

Usually this assignment is not immediately suitable for some carriers, because it has been built using partial information on their workload. For example, a carrier may not be willing to add to the current workload some pallets which must be collected from far satellites and/or delivered to far destinations. As a result, the forwarder needs to update the list of available vehicles and/or the revenues, and is required to quickly redetermine a new assignment according to the new data. Generally speaking, it is very important for the forwarder to determine feasible assignments within reasonably short time intervals.

The objectives of the paper are to:

- Present a mixed integer programming model for the above planning problem in the case of a real forwarder operating in an Italian seaport. The model aims at minimizing the overall assignment costs and to maximize the minimum load of the vehicles in second echelon, while enforcing the fulfillment of all transportation requests and the satisfaction of capacity constraints for vehicles and satellites.

- Propose a heuristic algorithm in order to obtain fast and high-quality solutions, when realistic-size model instances cannot be solved by a standard MILP solvers.

To our knowledge, such a problem setting has not been investigated so far in the literature. Significant research has been done on the cooperation of forwarders in dealing with single-echelon routing problems, as they are supposed to have their own fleets of trucks [3, 10, 14]. Transshipment facilities (or satellites) are considered for the first time in [2], but even in this study forwarders are supposed to own and control vehicles.

The paper is organized as follows. In Section 2 we introduce the optimization model for the forwarder planning problem in a two-echelon network. In Section 3 the heuristic algorithm is proposed to solve the problem. The numerical results on realistic test problems are reported in Section 4. Finally, in Section 5 results are summarized and some research perspectives are listed.

2 The Optimization Model

Consider a set $\mathcal{C}$ of inbound containers at a seaport. They are to be assigned to a set $\mathcal{S}$ of satellites located in the seaport hinterland, where pallets are unpacked from containers. In addition, let $\mathcal{K}$ be the set of vehicles available for the distribution of pallets from satellites and $\mathcal{U}$ be the set of consignees, where the pallets unpacked from the containers have their final destination. Let also $\mathcal{P}(c)$ be the set of pallets in container $c \in C$.

The following data are supposed to be known:

- V_s: maximum number of containers that can be handled at satellite $s \in \mathcal{S}$;

- r_c: number of pallets carried by container $c \in \mathcal{C}$;

- T_k: maximum number of pallets carried by vehicle $k \in \mathcal{K}$

The following set of decision variables is defined:

- x_{sc}: 1 if container $c \in \mathcal{C}$ is assigned to satellite $s \in \mathcal{S}$, 0 otherwise; let t_{sc} be the related unitary cost.
- w_{sk}: 1 if vehicle $k \in \mathcal{K}$ is assigned to satellite $s \in \mathcal{S}$ to perform the distribution in the second echelon, 0 otherwise; let h_{sk} be the related unitary cost.
- y_{scpk}: 1 if pallet $p \in P(c)$ of container $c \in \mathcal{C}$ is assigned to satellite $s \in S$ and vehicle $k \in \mathcal{K}$ for the distribution in the second echelon;
- $t_{\min}$: minimum number of pallets carried by vehicles selected for the distribution in the second echelon; let ρ be the weight of $t_{\min}$ in the objective function according to the forwarder policy.

In this model the costs of assigning containers to satellites (i.e. t_{sc}) account for the cost of moving each container from the port to satellite s, that of unpacking the container in that satellite, and that of moving each pallet unpacked from that container in the selected satellite to their consignees. The first two costs are embedded into f_{sc} for each pair $s \in \mathcal{S}$, $c \in \mathcal{C}$. The last cost depends on the distance between satellite and consignee, as well as on the value of the pallet shipped to the consignee. Therefore, we denote by $\Omega(c) \subseteq \mathcal{U}$ the set of consignees, who are expected to receive at least one pallet unpacked from container $c \in \mathcal{C}$, d_{su} the distance between satellite $s \in S$ and customer $u \in \mathcal{U}$, and b_u is an appropriate scale depending on consignee. Thus, we define:

$$t_{sc} \triangleq \left(f_{sc} + \sum_{u \in \Omega(c)} b_u d_{su} \right) , \tag{1}$$

The forwarder planning problem in a two-echelon network is then formulated as follows:

$$\min \sum_{s\in\mathcal{S}}\sum_{c\in\mathcal{C}} t_{sc}x_{sc} + \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} h_{sk}w_{sk} - \rho t_{\min} \tag{2}$$

s.t.

$$\sum_{s\in\mathcal{S}} x_{sc} = 1 \qquad c\in\mathcal{C} \tag{3}$$

$$\sum_{s\in\mathcal{S}} w_{sk} \le 1 \qquad k\in\mathcal{K} \tag{4}$$

$$\sum_{c\in\mathcal{C}} x_{sc} \le V_s \qquad s\in\mathcal{S} \tag{5}$$

$$\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} y_{scpk} = 1 \qquad c\in\mathcal{C}, p\in\mathcal{P}(c) \tag{6}$$

$$\sum_{k\in\mathcal{K}}\sum_{p\in\mathcal{P}(c)} y_{scpk} = r_c x_{sc} \qquad s\in\mathcal{S}, c\in\mathcal{C} \tag{7}$$

$$\sum_{c\in\mathcal{C}}\sum_{p\in\mathcal{P}(c)} y_{scpk} \le w_{sk}T_k \qquad s\in\mathcal{S}, k\in\mathcal{K} \tag{8}$$

$$t_{\min} \le \sum_{c\in\mathcal{C}}\sum_{p\in\mathcal{P}(c)} y_{scpk} + M(1-w_{sk}) \qquad s\in\mathcal{S}, k\in\mathcal{K} \tag{9}$$

$$x_{sc}\in\{0,1\} \qquad s\in\mathcal{S}, c\in\mathcal{C} \tag{10}$$

$$y_{scpk}\in\{0,1\} \qquad s\in\mathcal{S}, c\in\mathcal{C}, p\in\mathcal{P}(c), k\in\mathcal{K} \tag{11}$$

$$w_{sk}\in\{0,1\} \qquad s\in\mathcal{S}, k\in\mathcal{K} \tag{12}$$

$$t_{\min} \ge 0 \tag{13}$$

where $M = \max\{T_k : k\in\mathcal{K}\}$.

The rationale of the objective function is to minimize the container-satellite and vehicle-satellite total assignment costs, while maximizing the minimum load of the vehicles actually used. Note that the latter objective is also correlated to the minimization of the number of vehicles involved in the distribution.

Constraints (3) enforce that each container is assigned exactly to a satellite. Constraints (4) guarantee that each vehicle is assigned to a satellite at most. Constraints (5) enforce that each satellite serves a number of containers lower than its capacity. Constraints (6) make sure that each pallet in each container is picked up by a vehicle in a satellite. Moreover, (7) and (8) are linking constraints. In addition, constraints (8) enforce the capacity of vehicles in the second echelon. Owing to the "big M", constraints (9) are trivially satisfied in the case $w_{sk} = 0$, whereas, in the case $w_{sk} = 1$ they contribute to determine the workload of vehicle k and, thus, define the minimum workload $t_{\min}$. Finally, constraints (10)–(13) define the domain of the decision variables.

The following necessary feasibility conditions hold:

$$\sum_{s \in \mathcal{S}} V_s \geq |\mathcal{C}| \tag{14}$$

$$\sum_{k \in \mathcal{K}} T_k \geq |\mathcal{P}| \tag{15}$$

This model can be easily extended in order to account for possible additional restrictions imposed by carriers. For example, one can easily restrict the set of suitable satellites for each vehicle and penalize the unsuitable assignment of pallets to vehicles by introducing nonnnegative costs on y_{scpk} variables.

3 The heuristic algorithm

In order to solve the previous model, a heuristic algorithm is proposed. It is based on the fact that the assignment of containers to satellites plays the most critical role in terms of costs. In order to determine cost-effective assignments of containers to satellites, the proposed algorithm is based the relaxation of the previous model, where constraints (11) and (12) are modified as follows:

$$0 \leq y_{scpk} \leq 1 \qquad s \in \mathcal{S}, c \in \mathcal{C}, p \in \mathcal{P}(c), k \in \mathcal{K} \tag{16}$$

$$0 \leq w_{sk} \leq 1 \qquad s \in \mathcal{S}, k \in \mathcal{K} \tag{17}$$

Therefore, the modified model returns a lower bound on the optimal solution, in fact each container is assigned to a satellite, but some variables w_{sk} and y_{scpk} could be fractional.

In order to reestablish feasible values for variables w_{sk}, three rounding strategies are proposed:

1. Set all fractional w_{sk} variables to zero;
2. Set all fractional w_{sk} variables to one;
3. Round all fractional w_{sk} variables to the nearest integer value.

For each rounding strategy, the main steps of the algorithm are listed hereafter:

- Let $\mathcal{C}(s) \triangleq \{c \in \mathcal{C} : x_{sc} = 1\}$ and $\mathcal{K}(s) \triangleq \{k \in \mathcal{K} : w_{sk} = 1\}$ be the sets of containers and vehicles assigned to satellite $s \in S$, respectively.
- Calculate the difference Δ_s between the total capacity (in terms of pallets) of all vehicles assigned to $s \in S$ and the total number of pallets moved to $s \in S$ by containers, i.e:

$$\Delta_s \triangleq \sum_{k \in \mathcal{K}(s)} T_k - \sum_{c \in \mathcal{C}(s)} r_c. \tag{18}$$

- Order satellites by decreasing values of Δ_s.

- If $\Delta_s > 0$ (i.e. there is a surplus of vehicles in $s \in S$), order the vehicles in $\mathcal{K}(s)$ according to decreasing values of h_{sk}, remove them from the top of this ordered list and add them in a pool of not-assigned vehicles until Δ_s keeps being greater or equal then 0. If $\Delta_s < 0$ (i.e. there is a shortage of vehicles in $s \in S$), add to $\mathcal{K}(s)$ the vehicles with the largest capacity from the pool of not-assigned vehicles and stop when the condition $\Delta_s >= 0$ holds. If two vehicles with identical capacity could be added, select the vehicle with the minimum value of h_{sk}.

- For each satellite $s \in S$, solve the following restricted problem (RP^s), where y_{scpk} variables can be denoted y_{cpk}, $c \in \mathcal{C}(s), k \in K(s)$.

$$\max\ t^s_{min} \tag{19}$$

s.t.

$$\sum_{k\in\mathcal{K}(s)} \sum_{p\in\mathcal{P}(c)} y_{cpk} = r_c \qquad c \in \mathcal{C}(s) \tag{20}$$

$$\sum_{k\in\mathcal{K}(s)} y_{cpk} = 1 \qquad c \in \mathcal{C}(s), p \in \mathcal{P}(c) \tag{21}$$

$$\sum_{c\in\mathcal{C}(s)} \sum_{p\in\mathcal{P}(c)} y_{scpk} \leq T_k \qquad k \in \mathcal{K}(s) \tag{22}$$

$$t^s_{\min} \leq \sum_{c\in\mathcal{C}(s)} \sum_{p\in\mathcal{P}(c)} y_{cpk} \qquad k \in \mathcal{K}(s) \tag{23}$$

$$y_{cpk} \in \{0, 1\} \qquad c \in \mathcal{C}(s), p \in \mathcal{P}(c), k \in \mathcal{K}(s) \tag{24}$$

- Compute $t_{\min}$ be the minimum of all $t^s_{\min}$ among all satellites and set y_{scpk} equal to y_{cpk} for each satellite $s \in S$.

- Build a feasible solution of the original problem by collecting the current values of x_{sc}, w_{sk}, y_{scpk} and $t_{\min}$.

The best solution produced by each rounding strategy is taken.

4 Experimentation

This section aims to analyze the viability of the proposed algorithm in order to provide fast solutions for the model. The implementation of the proposed heuristic involves solving several subproblems. They have been faced by `CPLEX 12.7`, which has been compiled by Optimization Programming Language (`OPL`) and run single-threaded on a server with 8 processors (4 cores, 2.0 GHz), each with 16 GB of RAM, under a i686 GNU/Linux operating system. Moreover, the overall model has been implemented by `CPLEX 12.7` on the same server.

Several data must be initialized in order to implement the model. The number of containers $|\mathcal{C}|$ is erratic in daily operations. In order to come up with a realistic experimentation, three values of $|\mathcal{C}|$ are considered, according to the typical workload faced by the forwarder motivating this study:

- 25 containers, which represent the case of slack days;
- 50 containers, which represent the case of average days;
- 75 containers, which represent the case of peak days.

Since two types of containers are typically handled by the forwarder, we have set in our experimentation $\mathcal{C} = \bigcup_{i=1,2} \mathcal{C}_i$, where containers of type $\mathcal{C}_1$ and $\mathcal{C}_2$ carry up to 10 and 24 pallets, respectively. Since each container is supposed to be fully loaded, in this experimentation $r_c = 10$ if $c \in \mathcal{C}_1$ and $r_c = 24$ if $c \in \mathcal{C}_2$.

Since the percentage of the container types is also variable, we account for this percentage by the parameter *CntDst*. According to the forwarder's guidelines, two realistic scenarios of *CntDst* are considered. They are denoted by μ and ν and reported in Table 1, where $p_{ci}(\%)$, $i = 1, 2$, is the percentage of containers of type $\mathcal{C}_i$ arriving at the seaport and managed by the forwarder.

Table 1: Container mix

CntDst	μ	ν
$p_{c1}(\%)$	50	90
$p_{c2}(\%)$	50	10

Therefore, the overall numbers of pallets is:

$$|\mathcal{P}| = \sum_{c \in \mathcal{C}} r_c = r_{c1} p_{c1} |\mathcal{C}| + r_{c2} p_{c2} |\mathcal{C}| = |\mathcal{C}| \sum_{i=1}^{2} r_{ci} p_{ci} \, .$$

Two types of vehicles with different capacities are usually used in the second echelon to move pallets to their destinations. Therefore, set $\mathcal{K}$ has been partitioned into two subsets $\mathcal{K}_1$ and $\mathcal{K}_2$, where:

$$\left| \begin{array}{ll} T_k = 3, & \text{if } k \in \mathcal{K}_1 \\ T_k = 5, & \text{if } k \in \mathcal{K}_2 \end{array} \right.$$

Since the percentage of available vehicles is also erratic, we consider three possible configurations of this percentage, which is denoted by *VhcDst*. They are denoted by ϕ, χ and ψ, respectively, and reported in table 2, where p_{ki} represents the percentage of vehicles of type K_i for each scenario.

Table 2: Vehicle percentage

VhcDst	ϕ	χ	ψ
$p_{k1}(\%)$	25	50	75
$p_{k2}(\%)$	75	50	25

Therefore the overall capacity of vehicles is:

$$\sum_{k \in \mathcal{K}} T_k = |K| \sum_{i=1}^{2} T_i p_{ki} \, .$$

Because condition (15) must hold, i.e.

$$|K|\sum_{i=1}^{2} T_i p_{ki} \gg |\mathcal{C}|\sum_{i=1}^{2} r_{ci} p_{ci} = |\mathcal{P}|\,,$$

we set $|\mathcal{K}| = 1.5\left(|\mathcal{C}|\sum_{i=1}^{2} r_{ci}p_{ci}\right) / \left(\sum_{i=1}^{2} T_i p_{ki}\right)$. As a result, the dimension of instances is defined by the number of containers only.

Nevertheless, we need to set the cardinality of customers of set $\mathcal{U}$, in order to compute the assignment cost t_{sc} in (1). In this experimentation, $|\mathcal{U}|$ is determined as a percentage of $|\mathcal{P}|$. More precisely, three values of $|U|$ are considered: $|\mathcal{U}| = 20\%|\mathcal{P}|$, $|\mathcal{U}| = 50\%|\mathcal{P}|$ and $|\mathcal{U}| = 100\%|\mathcal{P}|$.

In this study the number $|\mathcal{S}|$ of satellites is set to 10 for all instances. The capacity V_s is supposed to be a random number between 10 and 100 in any satellite s, thus the condition (14) is always satisfied. The weighting parameter ρ in the objective function is set to 1.

The area served by the forwarder has been represented as a rectangle 100 km wide and 200 km high. The seaport is in the middle of one the shortest sides. The locations of satellites and customers and the initial positions of vehicles have been randomly generated within a rectangle in the range between 100 km and 150 km from the seaport. The costs h_{sk} of assignment of vehicles to satellites are supposed to be directly proportional to the distance between the position of vehicles and the location of satellites. The costs t_{sc} are computed by equation (1) according to the forwarder guidelines. More precisely:

- f_{sc} is set to be numerically equal to the distance in km between the seaport and satellite $s \in S$, because the transportation cost for each container is about 1 euro per km, whereas unpacking costs are supposed to be negligible as opposed to transportation costs in the considered range of distances.

- b_u is supposed to be equal for each customer $u \in \mathcal{U}$. Therefore, we set $b_u = b$ for each $u \in \mathcal{U}$. In this experimentation, b is supposed to take value 1.

Three groups of instances with 25, 50 and 75 containers have been generated and reported in tables 3, 4 and 5, together with the numerical results. The combination of all possible values *CntDst*, *VhcDst* and $|\mathcal{U}|$ results in 18 instances in each group. These tables report the instance (`Name`), the main data, i.e. the distribution of the types of containers (*CntDst*) and vehicles (*VhcDst*), and the number of customers $u \in \mathcal{U}$. In the columns denoted by `Cplex`, we report in the column (*Time [s]*) how many seconds it takes for Cplex to optimally solve the model and the optimality gap (*OptGap [%]*). The solver is set to stop after 1 hour running time or 0.01% optimality gap. When this time is larger than $1hour$, the symbol - is reported under the column *Time [s]*. When the first feasible solution is not determined within 1 hour, the symbol - is reported under the column (*OptGap [%]*).

In the columns denoted by `Heuristic`, we show how many seconds it takes for Cplex to compute the lower bound (*TimeLB [s]*), the best rounding strategy to obtain binary values for variables w_{sk} (*Rounding*), the overall running time of the heuristic algorithm (*Time [s]*) and the relative gap between the upper bound determined by Cplex and that of the heuristic (*Gap [%]*).

The experimentation shows that Cplex can optimally solve 17 out of 18 instances with 25 containers within the time limit. Although one cannot prove the optimality of instance P_9, the gap between lower and upper bound is very tight. The average solution time of these 17 instances is 360 seconds and it becomes 540 seconds if all 18 instances are considered. Generally speaking, these solution times are suitable for the forwarder, who wishes to complete the decision-making process within 10 minutes. However, in the case $|\mathcal{C}| = 50$ it is not possible to determine the optimal solution in 9 out of 18 instances and the average running time is about 2417 seconds, which is beyond the desired user-waiting time of the forwarder. In addition, optimality gaps are very poor in the case of instances P_{22}, P_{25}, P_{26} and P_{27}. In the case $|\mathcal{C}| = 75$, it is not possible to determine the first feasible solution in instances from P_{37} to P_{45} within 1 hour and only 3 instances can be solved to the optimum with an average waiting time of 3244 seconds. Therefore, the larger the instances, the lower the effectiveness of Clpex to support the forwarder.

According to these results, the experimentation of the proposed heuristic is of interest, as it can be used to solve all instances within adequate waiting times for the forwarder. More precisely:

- The instances with 25 containers can be solved within an average time of 19.13 seconds and have an average gap of 0.07 with respect to the solutions obtained by Cplex.
- The instances with 50 containers can be solved within an average time of 98.38 seconds and have an overall average gap of −9.11% with respect to the solutions obtained by Cplex. However, it is worth noting that the average gap is −41.06% in instances P_{22}, P_{25}, P_{26} and P_{27} and 0.02% in the other instances.
- The instances with 75 containers can be solved within an average time of 243.87 seconds. They have an average gap of 0.02% with respect to the 9 feasible solutions obtained by Cplex in the instances from P_{46} to P_{54}.

In addition, the experimentation shows that most of the running is devoted to the computation of the lower bound and all rounding strategies are able to lead to the best feasible solution in a short time. Therefore, it is recommended to keep all of them in the algorithm.

Last but not least, in almost all solutions of the heuristic, the minimum number of pallets carried by vehicles is equal to the capacity of the smallest vehicle type (3 pallets in this experimentation). Therefore, these solutions minimize the number of vehicles selected for the second echelon.

5 Conclusion

Despite the relevant role of forwarders in freight transportation, limited attention has been devoted to the development of optimization-based methods to support their complex activity, when they are not vehicle-equipped. To deal with this gap, a mixed integer programming model has been presented to investigate the motivating case-study of a forwarder operating in a two-echelon distribution network. The model minimizes the overall assignment costs and to maximize the minimum load of the vehicles in second echelon,

Table 3: Data and results for instances with $|\mathcal{C}| = 25$

Name	Data			Cplex		Heuristic			
	CntDst	*VhcDst*	$\|\mathcal{U}\|$	*Time [s]*	*OptGap [%]*	*timeLB [s]*	*Rounding*	*Time [s]*	*Gap [%]*
P_1	μ	ϕ	20%$\|\mathcal{P}\|$	480.33	0.01	17.77	1	23.21	0.07
P_2	μ	ϕ	50%$\|\mathcal{P}\|$	683.48	0.01	15.54	1,2,3	21.85	0.04
P_3	μ	ϕ	100%$\|\mathcal{P}\|$	197.52	0.01	15.20	1	22.29	0.07
P_4	μ	χ	20%$\|\mathcal{P}\|$	242.70	0.01	19.75	1,3	25.34	0.05
P_5	μ	χ	50%$\|\mathcal{P}\|$	204.36	0.01	17.99	1,3	24.76	0.05
P_6	μ	χ	100%$\|\mathcal{P}\|$	637.55	0.01	18.50	1,3	26.19	0.15
P_7	μ	ψ	20%$\|\mathcal{P}\|$	441.34	0.01	21.05	1,3	27.74	0.08
P_8	μ	ψ	50%$\|\mathcal{P}\|$	425.80	0.01	23.02	1,2,3	30.39	0.00
P_9	μ	ψ	100%$\|\mathcal{P}\|$	-	0.01	25.48	1,3	35.11	0.15
P_{10}	ν	ϕ	20%$\|\mathcal{P}\|$	56.43	0.01	6.39	1	9.48	0.06
P_{11}	ν	ϕ	50%$\|\mathcal{P}\|$	1338.79	0.01	6.42	1,3	9.88	0.12
P_{12}	ν	ϕ	100%$\|\mathcal{P}\|$	101.00	0.01	6.37	1,3	10.76	0.01
P_{13}	ν	χ	20%$\|\mathcal{P}\|$	124.10	0.01	7.91	1	11.16	0.04
P_{14}	ν	χ	50%$\|\mathcal{P}\|$	100.11	0.01	7.68	1,3	11.46	0.14
P_{15}	ν	χ	100%$\|\mathcal{P}\|$	128.03	0.01	9.92	3	14.87	0.04
P_{16}	ν	ψ	20%$\|\mathcal{P}\|$	190.48	0.01	8.80	1,3	12.41	0.09
P_{17}	ν	ψ	50%$\|\mathcal{P}\|$	684.42	0.01	9.80	1,3	13.92	0.19
P_{18}	ν	ψ	100%$\|\mathcal{P}\|$	77.07	0.01	8.81	1,3	13.59	0.01

Table 4: Data and results for instances with $|\mathcal{C}| = 50$

Name	Data			Cplex		Heuristic			
	CntDst	*VhcDst*	$\|\mathcal{U}\|$	*Time [s]*	*OptGap [%]*	*timeLB [s]*	*Rounding*	*Time [s]*	*Gap [%]*
P_{19}	μ	ϕ	20%$\|\mathcal{P}\|$	-	0.02	88.96	1	109.22	0.02
P_{20}	μ	ϕ	50%$\|\mathcal{P}\|$	2942.67	0.01	83.70	1	106.29	0.04
P_{21}	μ	ϕ	100%$\|\mathcal{P}\|$	-	0.02	84.82	1	113.11	0.03
P_{22}	μ	χ	20%$\|\mathcal{P}\|$	-	65.72	133.24	1,3	155.50	-39.64
P_{23}	μ	χ	50%$\|\mathcal{P}\|$	-	0.01	100.11	1,3	125.52	0.00
P_{24}	μ	χ	100%$\|\mathcal{P}\|$	-	0.07	92.82	1,3	122.09	-0.02
P_{25}	μ	ψ	20%$\|\mathcal{P}\|$	-	71.27	174.71	3	200.85	-41.57
P_{26}	μ	ψ	50%$\|\mathcal{P}\|$	-	70.71	117.22	1	146.06	-41.40
P_{27}	μ	ψ	100%$\|\mathcal{P}\|$	-	71.29	117.57	1	151.46	-41.61
P_{28}	ν	ϕ	20%$\|\mathcal{P}\|$	1055.06	0.01	33.93	1,3	45.00	0.01
P_{29}	ν	ϕ	50%$\|\mathcal{P}\|$	1582.45	0.01	34.95	1,3	47.35	0.05
P_{30}	ν	ϕ	100%$\|\mathcal{P}\|$	1152.75	0.01	33.67	1,3	48.50	0.03
P_{31}	ν	χ	20%$\|\mathcal{P}\|$	578.63	0.01	56.12	1	69.75	0.00
P_{32}	ν	χ	50%$\|\mathcal{P}\|$	567.07	0.01	39.05	1	52.65	0.04
P_{33}	ν	χ	100%$\|\mathcal{P}\|$	1398.42	0.01	43.75	1	60.15	0.02
P_{34}	ν	ψ	20%$\|\mathcal{P}\|$	-	0.04	47.09	3	59.92	0.03
P_{35}	ν	ψ	50%$\|\mathcal{P}\|$	968.12	0.01	72.57	1	91.65	0.04
P_{36}	ν	ψ	100%$\|\mathcal{P}\|$	859.15	0.01	48.22	1	65.75	0.04

Table 5: Data and results for instances with $|\mathcal{C}| = 75$

Name	Data			Cplex		Heuristic			
	CntDst	*VhcDst*	$\vert\mathcal{U}\vert$	*Time [s]*	*OptGap [%]*	*timeLB [s]*	*Rounding*	*Time [s]*	*Gap [%]*
P_{37}	μ	ϕ	$20\%\vert\mathcal{P}\vert$	-	-	240.21	1,3	284.17	-
P_{38}	μ	ϕ	$50\%\vert\mathcal{P}\vert$	-	-	240.50	1,3	289.23	-
P_{39}	μ	ϕ	$100\%\vert\mathcal{P}\vert$	-	-	240.86	1,3	296.77	-
P_{40}	μ	χ	$20\%\vert\mathcal{P}\vert$	-	-	291.71	1,3	338.41	-
P_{41}	μ	χ	$50\%\vert\mathcal{P}\vert$	-	-	286.06	1,3	344.09	-
P_{42}	μ	χ	$100\%\vert\mathcal{P}\vert$	-	-	284.79	1,3	352.13	-
P_{43}	μ	ψ	$20\%\vert\mathcal{P}\vert$	-	-	356.88	1	417.80	-
P_{44}	μ	ψ	$50\%\vert\mathcal{P}\vert$	-	-	356.57	1,2,3	415.94	-
P_{45}	μ	ψ	$100\%\vert\mathcal{P}\vert$	-	-	367.67	1	441.68	-
P_{46}	ν	ϕ	$20\%\vert\mathcal{P}\vert$	-	0.02	87.62	1,3	110.37	0.03
P_{47}	ν	ϕ	$50\%\vert\mathcal{P}\vert$	3457.07	0.01	87.40	1	113.98	0.01
P_{48}	ν	ϕ	$100\%\vert\mathcal{P}\vert$	2837.47	0.01	86.00	1,3	117.94	0.03
P_{49}	ν	χ	$20\%\vert\mathcal{P}\vert$	-	0.03	99.12	1	123.89	0.00
P_{50}	ν	χ	$50\%\vert\mathcal{P}\vert$	-	0.04	100.58	1	128.99	0.02
P_{51}	ν	χ	$100\%\vert\mathcal{P}\vert$	-	0.04	114.19	1	144.07	0.02
P_{52}	ν	ψ	$20\%\vert\mathcal{P}\vert$	-	0.03	105.64	1	141.81	0.00
P_{53}	ν	ψ	$50\%\vert\mathcal{P}\vert$	-	0.03	132.65	3	164.70	0.02
P_{54}	ν	ψ	$100\%\vert\mathcal{P}\vert$	3437.74	0.01	126.51	1	163.74	0.04

while enforcing the fulfillment of all transportation requests and the satisfaction of capacity constraints for vehicles and satellites. The definition of the costs to be embedded into the objective function has been tailored for this model according to the guidelines of a real forwarder.

Since realistic-size model instances cannot be solved by Cplex within an acceptable time interval, a three-step heuristic algorithm is proposed. In the first step a lower bound is determined by the solution of a relaxed model in which only the variables assigning containers to satellites are kept as boolean and the other variables are continuos. In the second step, a feasible assignment of vehicles to satellites is determined by rounding fractional variables according to three rounding rules. In the third step, an auxiliary optimization model is solved for each satellite and each rounding rule in order to determine the remaining variables. The final solution is the best among those associated with the three rounding rules. The experimentation shows that this algorithm can be adopted to obtain fast and high-quality solutions as opposed to an off-the-shelf optimization solver.

Research developments will be carried out to incorporate the non-linear relation between the quantity of pallets assigned to carriers and the related assignment costs in the case of vehicles larger than those considered in this paper. Finally, a more detailed city-logistics problem will be investigated in order to minimize both the costs of forwarders and carriers in the case of maritime urban areas.

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