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Assessing the benefits of using swap locations in the Pickup and Delivery Problem

Mathematical formulation and computational experiments

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Abstract

In a globalizing world economy, logistics providers have to create solutions to satisfy customer's requests while meeting environmental requirements and ensuring low costs of transport. To this end, the Pickup and Delivery Problem (PDP) aims at designing routes such that the distance traveled empty is as short as possible, given a set of transportation requests. In this strategy, driving time constraint appears to be a key success factor since it restricts the number of round trip opportunities for each vehicle. To overcome time pressure, it could be interesting for drivers to share the deliveries by swapping their cargo along the way. In this paper, we evaluate the benefits of using swap locations in the Pickup and Delivery Problem. To achieve this, we present the Swap-Body Pickup and Delivery Problem (SBPDP) as a variant of the PDP in which intermediate locations can be used by vehicles to swap their trailers. A mixed integer programming formulation is proposed and computational experiments are conducted so that we can assess the merits of our swap-body approach, comparatively with a classical stay-with version of the PDP. We find that enabling swap locations appears to be of real interest when an average transportation request consumes at least 23% of the available time. Finally, our model allows fleet to maintain the best level of empty trips reduction (-54%), even under increasing time pressure, i.e. when lead time decreases or when distance to be covered increases – two challenges posed by the extent of trade globalization.

Keywords : Pickup and Delivery; Truck and Trailer; Swap-Body; Routing problem

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1. Introduction

Global trade has grown considerably over the last two decades bringing with it changes on different levels of logistics decision making, i.e. strategic, tactical and operational. Firms have to create solutions to meet the demands of the supply chain customer, support the achievement of societal challenges while ensuring low costs of transport (Mason et al., 2019). The development of online commerce and the fierce global competition have opened up profound new challenges. Consumers expect to get their products on time which implies tighter delivery windows and more frequent deliveries of smaller batch sizes. Add to this the longer distances traveled due to the extent of trade globalization such that logistic providers have to move smaller volume on larger distances, more frequently (Belenguer et al., 2016).

At the same time, logistics players are operating within exceedingly tight profit margins which puts them under massive commercial pressure. Consequently, reducing transport costs has become a major issue, much of which is attributable to physical distribution only, i.e. the transport of goods from distribution centers to customers (Gerdessen, 1996).

Finally, the transportation industry has to consider general society expectations regarding both economic growth and sustainability. As responsible for around a quarter of the EU-28 greenhouse gas emissions (2019), the transport sector needs to meet the long-term 60% greenhouse gas emission reduction target as set out in the 2011 Transport White Paper.

To achieve this, besides the expected improvement in energy efficiency and electrification of vehicles, it is necessary to increase the efficiency of the logistics system as a whole (Creemers et al., 2017). An important source of improvement is the reduction of empty hauls. In 2010, the European Commission reported that they represent 27.3% of the national road freight kilometers.

Considering all this, it is obvious that the original “one line, two points” illustrated in the left panel of Figure 1 can not meet the requirements of current issues since this implies that half of the trips would be traveled empty. Instead, fleet companies consider at least round trip opportunities to avoid empty back-hauling by making a tour that consists of three or more stops, as shown in the middle panel of Figure 1.

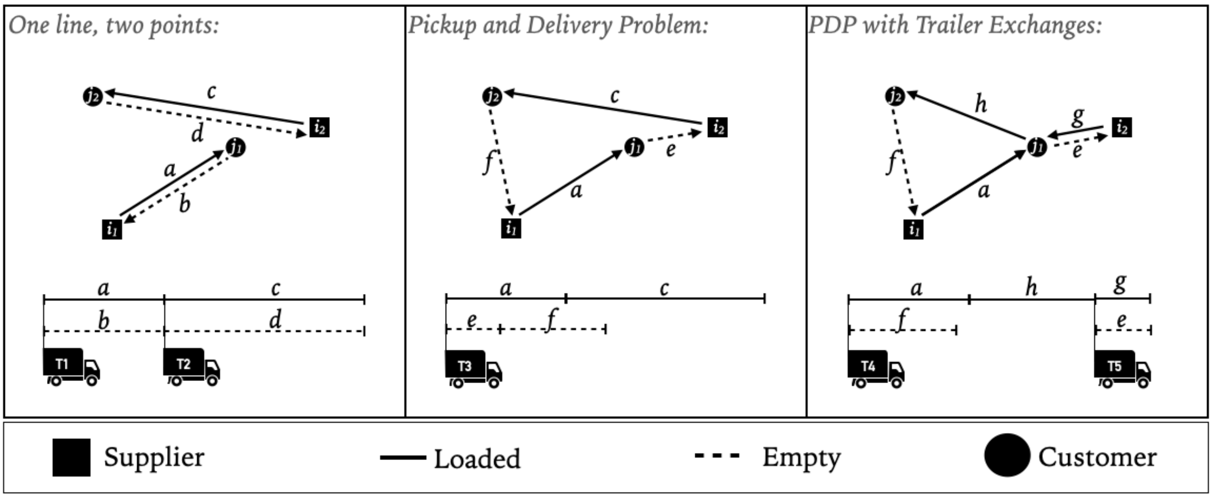


Figure 1 : Illustration of the General Pickup and Delivery Problem, with trailer exchanges

To that end, the Pickup and Delivery Problem (PDP) is a strategy characterized by a set of transportation requests where each load has to be transported by one vehicle from its origin '*i*' where it is to be picked up, to its destination '*j*' where it is to be delivered (Savelsbergh et al., 1995). The objective is to design routes to meet customer demands in such way that the empty distance covered is as short as possible. The impact of PDP on distance reduction appears clearly on Figure 1 as empty hauls are reduced from $b+d$ to $e+f$.

In such strategy, driving time limit appears to be a key success factor since it restricts the length of a tour that can be done by a single truck. For instance, given a certain time pressure, vehicle *T3* may no longer be able to complete its tour. In such case, we would have no choice but to ship the goods with trucks *T1* and *T2* as in the initial situation.

To circumvent this problem, we propose an extension of the PDP in which intermediate locations can be used for trucks to swap their trailers. For example, the right panel of Figure 1 illustrates a truck *T5* that collects the load at the supplier 'i_2', drops it at the customer 'j_1', where truck *T4* carries the load to the customer 'j_2'.

Allowing a request to be served by several vehicles provides the advantages of the routing optimization in terms of empty trips reduction, while each truck respects its own driving time limit by sharing deliveries on excessively long routes.

In this study, we propose a mathematical model describing a Pickup and Delivery Problem with trailer exchanges. Numerical experiments are carried out to determine the response of our model to variation of time pressure, in comparison with a classical stay-with version of the Pickup and Delivery Problem.

The rest of this paper is organized as follows. In the next section, we give the literature overview regarding models related to the routing problem with trailers. In Section 3, several assumptions are made and we build a mathematical integer programming model as a combination of Pickup and Delivery Problem with Network Design model. The scope and the limitations of this study are discussed. In Section 4, we present our computational experiments based on real instances and the characteristics that influence the benefits of using swap locations are investigated. Finally, we conclude in Section 5 and propose future research directions.

2. Literature review

To the best of our knowledge, no additional studies addressing the Pickup and Delivery Problem with trailer exchanges have been published to date. However, we have identified three relevant types of routing problems taking trailers into account as a detachable part of the truck: the Drop-and-Pull transport organization, the Truck and Trailer Routing Problem and the Swap-Body Vehicle Routing Problem.

In this section, we offer an overview of these three adjacent models and we demonstrate our contribution in the literature by highlighting the differences with our approach.

2.1 Drop-and-Pull transport

Because cargo loading and unloading time heavily decrease the utilization ratio of general container trucks (Xu et al., 2019), trailer switching points could allow fleets to reduce that handling time by quickly drop a trailer, put on another one or keep unload for the next task, allowing the driver to avoid wasting time waiting (Faria et al., 2019). In that purpose, Drop-and-Pull (D-P) transport is an advanced transport organization model that can help logistics companies to reduce operating costs by improving the efficiency of the tractor and increasing the related revenue (Yang et al., 2018). A D-P strategy starts when semi-trailers can be handled independently of the traction unit of the trucks, which makes the transport system more agile (Faria et al., 2019). A problem of scheduling tractor-and-trailer transport of heavy and empty containers is proposed: even if the transfer of empty trailers between nodes does not bring practical utility, it is necessary to ensure the later operation of the system (Yang et al., 2016). In that sense, Wang et al. (2019) shown that a double trailer D-P can reduce the transportation costs by 13.4% compared to a single trailer D-P. Xu et al. (2020) proposed a sensitivity analysis on the number of tractors, revealing that it can not be increased too much. In the same time, the site of switching station must be selected properly as the efficiency of the D-P transport network hinges directly on the planning of the so-called shared freight station (Feng et al., 2019). Other aspects have also been investigated such as the general vehicle performance (Zhao et al., 2018) and the whole process management with the use of IoT technologies required for the elaboration of efficient D-P strategies (Li et al., 2013).

2.2 Truck and Trailer Routing Problem

First of all, we must define the Vehicle Routing Problem (VRP) as a particular PDP in which either all the origins or all the destinations are located at the depot (Savelsbergh et al., 1995). To put it simply, a truck starts from a single distribution center, from which it delivers a series of customers, one after the other, such that the total cost is as low as possible.

An extension of the VRP with the consideration of trailers was first investigated by Semet & Taillard (1993). Sometimes, various traffic situations do not allow long vehicles (i.e. a truck pulling a trailer) to reach their depot, especially in the remote mountainous area or in the crowded downtown (Bian et al., 2016) where space is not always available for maneuvering. Therefore, Semet (1995) introduced the Partial Accessibility Constrained Vehicle Routing Problem (PACVRP) to allow a vehicle to leave its trailer at a parking place and visit some difficult customers with its maneuverable truck only. In this problem, each grocery store must be delivered by a subset of trucks and trailers during a time window and an integer programming formulation is used to determine the number of trailers needed, given an available number of heterogeneous trucks and their volume capacity, by minimizing the total cost of vehicles team.

The Vehicle Routing Problem with Trailers (VRPT) proposed by Gerdessen (1996) is slightly different, in that it does not consider any accessibility constraints; all customers may be served by a complete vehicle. Instead, considering that time and trouble could be saved, it encourages the truck to travel alone by minimizing the maneuvering time, defined as the additional time required by complete vehicle as opposed to trucks alone (Toffolo et al., 2018). In this way, customers located in difficult areas are modeled with larger maneuvering times (Rothenbächer et al., 2018). In such case, we can envisage that some trailers are left at parking places several times while some are not left at a parking place at all.

As a generalization of the VRPT, Chao (2002) addressed the Truck and Trailer Routing Problem (TTRP) in which a fixed fleet composed of m trucks and n trailers ($m \geq n$) serves two types of customers: a "truck customer" that have limited maneuvering space and can only be served by a truck, and a "vehicle customer" that can be served either by a truck with or without an attached trailer. Each customer location can be used as a parking place.

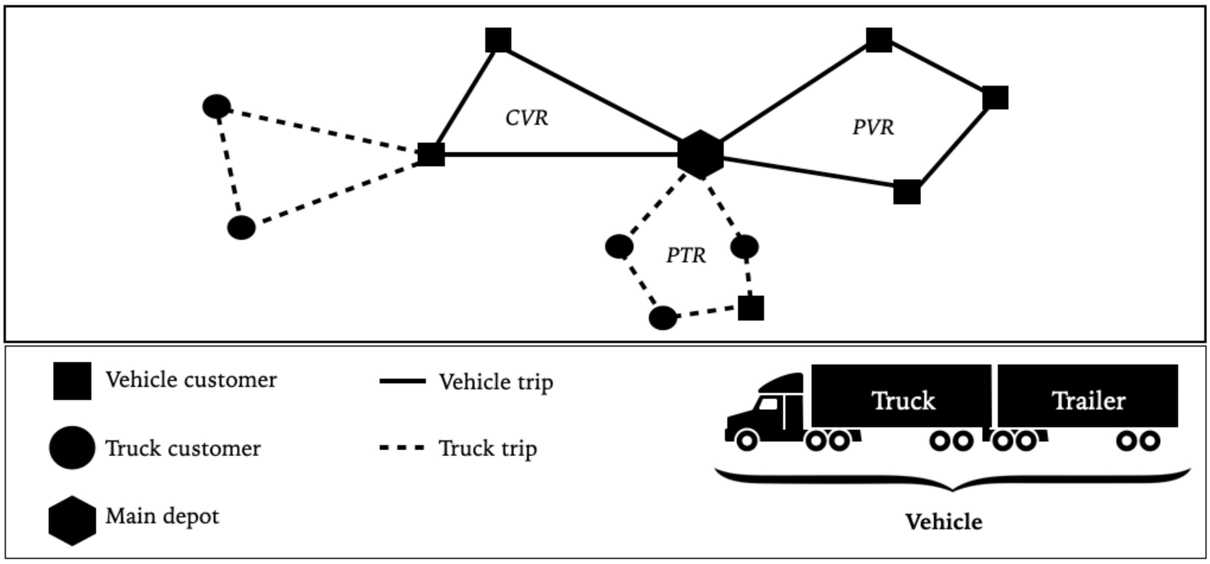


Figure 2: Types of route in the Truck and Trailer Routing Problem

Three types of routes can be defined as illustrated in Figure 2: (1) a pure truck route (PTR) traveled by a single truck; (2) a pure vehicle route (PVR) without any sub-tour traveled by a complete vehicle; and (3) a complete vehicle route (CVR) consisting of a main tour traveled by a complete vehicle, and at least one sub-tour traveled by the truck alone (Lin et al., 2009).

A sub-tour occurs when the trailer is dropped off at a vehicle customer location (sub-tour root) while the truck proceeds to service truck customers.

The TTRP is not subject to any time constraints and its objective is to find a route that minimizes the total distance traveled by the fleet (Lum et al., 2015) such that the total demand of any vehicle route does not exceed the total capacity of the vehicles used in that route (Todosijević et al., 2017).

This approach constitutes a challenging problem with significant practical relevance for a range of distribution activities with accessibility constraints as it ensures efficiency with regard to a number of economic and ecological factors. Some authors (Derigs et al., 2013) aimed at demonstrating its value in milk collection. Because of high milk production rates and large distances between dairy and farms, trucks are forced to increase the total vehicle capacity. Yet, some farms can only be reached by narrow roads and small bridges (Gerdessen, 1996), making it impossible for a truck- and trailer- combination to pass (Drexl et al., 2018). Another application area can be found in the distribution of compound animal feed in rural areas.

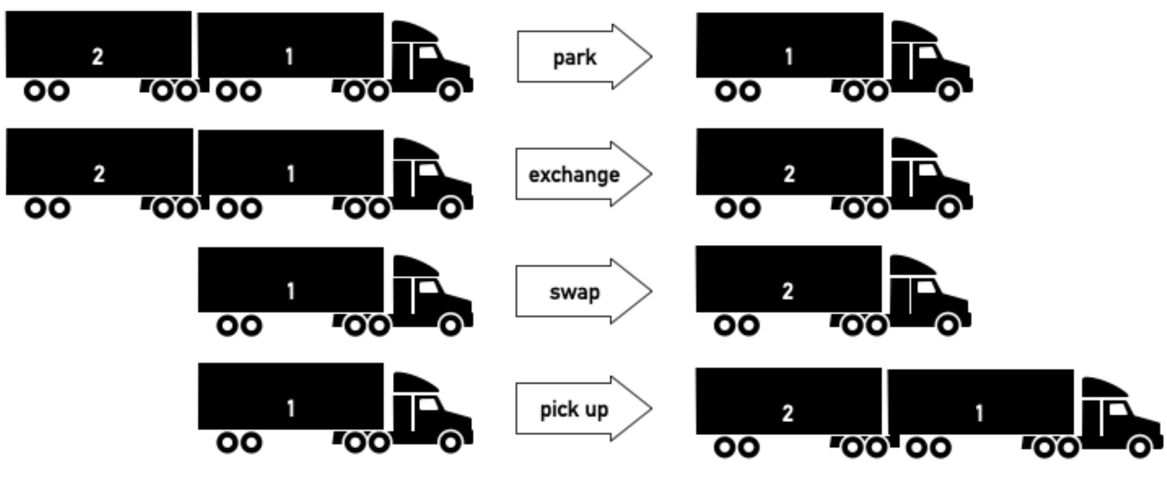
2.3 Swap-Body Vehicle Routing Problem

Although the use of intermediate locations to change a vehicle configuration on the way dates back several decades ago, it has attracted increased attention for the research community only in the last few years (Rothenbächer et al., 2018) with the recently variant of Vehicle Routing Problem with Swap Bodies (SB-VRP) proposed by the EURO Working Group on Vehicle Routing and Logistics Optimization (VeRoLog).

Such as the TTRP, it considers a homogeneous fleet of vehicles whose sizes may be enlarged via the addition of a swap body (trailer). While doubling capacity, the inclusion of a swap body also increases its operational cost (Toffolo et al., 2018). For the latter, special depots, called swap locations, can be used to perform several actions as illustrated in Figure 3. Again, customers are distinguished between truck- and train- customers accordingly to their accessibility, and they are delivered only once.

To sum up, the SB-VRP can be defined as the search for a cost minimal set of routes under some accessibility restrictions. Because those problems are a generalization of the VRP, they are also NP-hard, and research has mainly focused on finding constructive algorithms and evaluate their performance.

Figure 3: Types of operation in the Swap-Body Vehicle Routing Problem



Park action : a truck drops the back swap body of the train

Exchange action : a truck drops the front swap body of the train

Swap action : a truck drops the currently attached swap body and picks up another swap-body parked at an earlier stage

Pick Up action : a truck picks up the swap-body parked at an earlier stage

In conclusion, several routing problems with the consideration of trailers have been studied in the literature. On one hand, the TTRP and the SB-VRP consider swapping locations as an opportunity for vehicles to drop off their trailer in order to reach customers in restricted areas. On the other hand the D-P model aims to eliminate waiting times of drivers when loading/unloading cargoes by quickly dropping their trailer at a customer point.

The purpose of this paper is to contribute to the development of a different approach that considers the swap locations as a way to reduce the impact of driving time constraints on routes optimization. In fact, in our case we do not assume any accessibility constraints. Moreover, we suppose an equivalent average handling time whether it is to load, unload or exchange trailers. Unlike the previous models, therefore, the advantage of swapping trailers no longer lies in accessing difficult areas, nor in the time saved by drivers during loading/unloading, but rather in the design of an agile and intelligent distribution network that offers more flexibility and allows better distance reduction under time pressure.

To achieve this, we build a mathematical model representing a PDP in which swap actions are allowed, described as the Swap-Body Pickup and Delivery Problem (SBPDP). Numerical experiments are conducted using both the PDP and our SBPDP in order to assess the merits of swap actions on trips reduction.

3. Problem description and modeling

In this section, we provide the details of our approach to develop our Swap-Body Pickup and Delivery Problem formulation as a combination of a Network Design model and a classical Pickup and Delivery Problem.

3.1 Problem settings

Given a set of transportation requests where each load has to be transported from its origin '*i*' to its destination '*j*', a commodity '*k*' might represent distinct physical goods or the same physical good, but with different points of origin and destination (Sheffi et al., 1984).

All requests are known and the objective of our model is to determine a set of routes (i.e. a tour) that minimizes the total distance traveled. Each truck has to respect a certain driving time limit that restricts the length of the tours.

It has already been shown in Figure 1 that it could be interesting to transit cargoes via swap locations to circumvent the driving time limit. Therefore, our SBPDP should allow every commodities to be delivered from the supplier to the consumer, whether it is a straight delivery or by means of transshipments in swap locations.

To ensure interoperability between trucks and trailers, we assume a fleet of homogeneous and standardized vehicles with a configuration consisting of a traction unit (truck) separate from the load units (trailers). Drivers are allowed to park, pick-up or swap their trailers at any nodes, i.e. supplier and customer locations.

To tackle this NP-hard Problem, we propose an integer programming-based model which consists of a classical PDP with flow conservation equations adapted from Network Design model. In the following, we first present a modeling for the classical PDP, then we introduce a Network Design model, to finally build our SBPDP model.

3.2 Notations

In this section, we present the indexes and the parameters used in our models.

Indexes :

$k = \{1, \dots, S_K\}$ for the set of commodities;

$i = \{1, \dots, S_N\}$ for the set of suppliers;

$j = \{1, \dots, S_N\}$ for the set of customers;

$v = \{1, \dots, S_V\}$ for the set of vehicles;

Parameters :

$Dist_{ij}$: the distance between any two nodes *i* and *j* (km);

$Speed$: the average speed of the truck (km/h);

O_k : the point of origin for commodity *k*;

R_k : the required quantity for commodity *k*;

D_k : the point of destination for commodity *k*;

$Thdl$: the time spent handling cargo (h);

$Tmax$: the maximal driving time for each driver (h);

3.3 Pickup and Delivery Problem (PDP)

The PDP is characterized by a set of commodities to be transported by a set of vehicles from a set of origins directly to a set of destinations. Empty back-hauling trips are decided such that the empty distance covered is as short as possible. To tackle this NP-hard problem, we propose a Mixed Integer Programming formulation as follows.

Decision variables :

x_{ij}^{v} : the number of loaded trips from *i* to *j* by vehicle *v*;

y_{ji}^{v} : the number of empty trips from *j* to *i* by vehicle *v*;

Mathematical formulation :

$$min \sum_{i,j,v} Dist_{ij} * \left(x_{ij}^{v} + y_{ji}^{v}\right) \tag{1}$$

Subject to :

$$\sum_{v} x_{ij}^{v} = R_k \qquad \forall\, k \in S_{K,} i = O_k, j = D_k \tag{2}$$

$$\sum_{j,v} \left(x_{ij}^{v} + y_{ij}^{v}\right) = \sum_{j,v} \left(x_{ji}^{v} + y_{ji}^{v}\right) \forall\, i \in S_N \tag{3}$$

$$\sum_{i,v} \left(x_{ij}^{v} + y_{ij}^{v}\right) = \sum_{i,v} \left(x_{ji}^{v} + y_{ji}^{v}\right) \forall\, j \in S_N \tag{4}$$

$$\sum_{i,j} (x_{ij}^{v} + y_{ji}^{v}) * \left(\frac{Dist_{ij}}{Speed} + Thdl\right) \leq Tmax \forall \quad v \in S_V \tag{5}$$

$$x_{ij}^{v}, y_{ji}^{v} \in \mathbb{Z}^{+} \qquad \forall\, i, j \in S_N, v \in S_V \tag{6}$$

The objective (1) is to minimize the total distance composed of loaded and empty trips. Constraint (2) stipulates that all demands for a commodity *k* should be satisfied from its point of origin directly to its point of destination, so that the only potential for improvement is based on back-hauling trips. Basic flow conservation constraint (3) ensures each vehicle that departs from a node finally returns back to it, while (4) ensures each vehicle that arrives to a node ultimately gets out of it. Constraint (5) prevents any driver to work more than his weekly driving time limit *Tmax*, considering the handling time spent for loading/unloading its cargo whenever he steps into a node.

Note that, in the interests of saving computing time, subtour elimination constraints have not been included in the model. That being so, we are not able to ensure the connectedness of solutions and it may happen that a single truck covers two disjoint and unconnected tours, such that the impact of driving time limit tends to be underestimated.

3.4 Network design model

Network design models aim to chose which arcs (*i,j*) of capacity K_{ij} to include in a transportation network while assigning them a fixed construction cost c_{ij}. This can help to support decision-making for strategic capital investment involving long-term infrastructure such as highway or airport (Magnanti et al., 1984). The problem can be stated as follows.

Decision variables :

x_{ij}: 1 if arc (*i,j*) is chosen, 0 otherwise;

f_{ij}^k : the flow of commodity *k* on arc (*i,j*);

Mathematical formulation :

$$min \sum_{i,j} c_{ij} * x_{ij} \qquad (7)$$

Subject to :

$$\sum_{j \in S_N} f_{ij}^k - \sum_{l \in S_N} f_{li}^k = \begin{cases} R_k & \text{if } i = O_k \\ -R_k & \text{if } i = D_k \\ 0 \; otherwise \end{cases} \forall\, k \in S_K \qquad (8)$$

$$\sum_k f_{ij}^k \leq K_{ij} * x_{ij} \quad \forall\, i,j \in S_N \qquad (9)$$

$$f_{ij}^k \geq 0, x_{ij} \in \{0,1\} \quad \forall\, i,j \in S_N, k \in S_K \qquad (10)$$

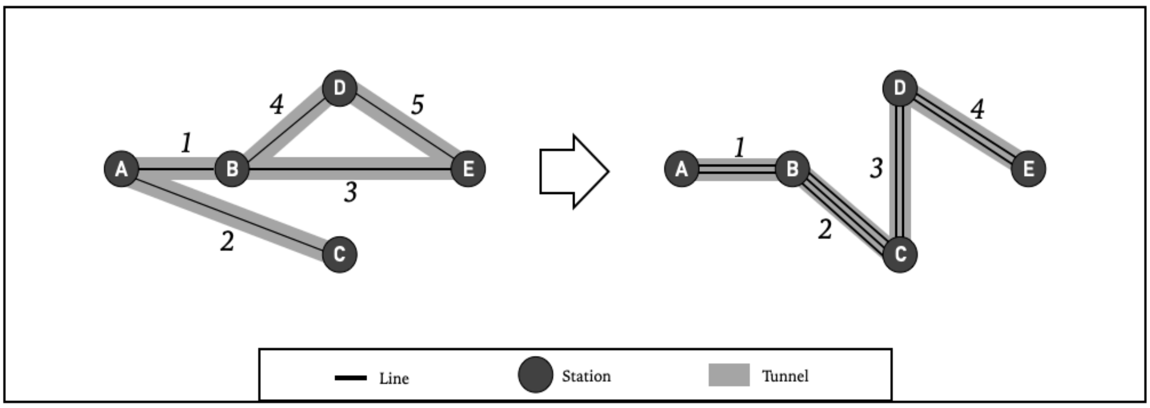
The objective (7) minimizes the construction cost of the network. Network flow conservation constraint (8) stipulates that the $(out - in)$ differential of flows for a commodity *k* should be equal to the required amount of flow for that commodity in its point of origin. Analogously, the $(in - out)$ differential of flows for a commodity *k* should be equal to the required amount of flow for that commodity in its point of destination. In other words, for each commodity *k,* the point of origin should ultimately eject the exact amount R_K of that commodity while its point of destination should ultimately absorb it. In every other nodes, the differential $(in - out)$ is equal to zero. Finally, constraint (9) states that the arc (*i*,*j*) has to be built to allow a flow from node *i* to *j*, while the total flow f_{ij} can not exceed the capacity K_{ij} of that arc.

3.5 Swap-Body Pickup and Delivery Problem (SBPDP)

In the following, we build an extension of the PDP in which trucks are allowed to transit their cargo through some swap locations rather than shipping it directly to the end customer, provided that another truck takes care of the rest of the trip.

The issue with the PDP is that vehicles are not allowed to achieve any other actions than loading/unloading. There is no question of exchanging trailers since drivers do not even have the opportunity to make any deviation, due to basic demand satisfaction constraint (2) that forces them to fulfill their mission strictly, from a point of origin directly to a point destination. Network design constraints will help us working around this. In fact, an interesting property of this model is illustrated in Figure 4. In this example, we assume a fixed cost for each tunnel dug. By doing so, the optimal network gives the minimum required amount of tunnels to connect every metro stations with the appropriate lines. Note that some lines initially required between two stations can now transit through other nodes.

Figure 4: Example of network design application to connect metro stations



For instance, the line required between A and C is now replaced by two lines: one between A and B and one between B and C. This is possible thanks to the network flow conservation constraint (8) that ensures each destination to be served by its origin, whether directly or via any transit points.

Finally, introducing a network flow conservation constraint will help us enhancing the flexibility of the PDP by allowing vehicles to make some detours, meet at some points and eventually swap their trailers. Our SBPDP model can be formulated as follows.

Decision variables :

x_{ij}^{v} : the number of loaded trips from *i* to *j* by *v*;

y_{ji}^{v} : the number of empty trips from *j* to *i* by *v*;

f_{ij}^{k} : the flow of commodity *k* on arc (*i,j*);

Mathematical formulation :

$$min \sum_{i,j,v} Dist_{ij} * \left(x_{ij}^{v} + y_{ji}^{v}\right) \tag{11}$$

Subject to :

$$\sum_{j \in S_N} f_{ij}^{k} - \sum_{l \in S_N} f_{li}^{k} = \begin{cases} R_k & \text{if } i = O_k \\ -R_k & \text{if } i = D_k \\ 0 \; otherwise & \end{cases} \forall\, k \in S_K \tag{12}$$

$$\sum_{v} x_{ij}^{v} = \sum_{k} f_{ij}^{k} \qquad \forall\, i,j = S_N \tag{13}$$

$$\sum_{j,v} \left(x_{ij}^{v} + y_{ij}^{v}\right) = \sum_{j,v} \left(x_{ji}^{v} + y_{ji}^{v}\right) \forall\, i \in S_N \tag{14}$$

$$\sum_{i,v} \left(x_{ij}^{v} + y_{ij}^{v}\right) = \sum_{i,v} \left(x_{ji}^{v} + y_{ji}^{v}\right) \forall\, j \in S_N \tag{15}$$

$$\sum_{i,j} (x_{ij}^{v} + y_{ji}^{v}) * \left(\frac{Dist_{ij}}{Speed} + Thdl\right) \leq Tmax \qquad \forall\, v \in S_V \tag{16}$$

$$x_{ij}^{v}, y_{ji}^{v} \in \mathbb{Z}^{+} \qquad \forall\, i,j \in S_N, v \in S_V \tag{17}$$

$$f_{ij}^{k} \geq 0 \qquad \forall\, i,j \in S_N, k \in S_K \tag{18}$$

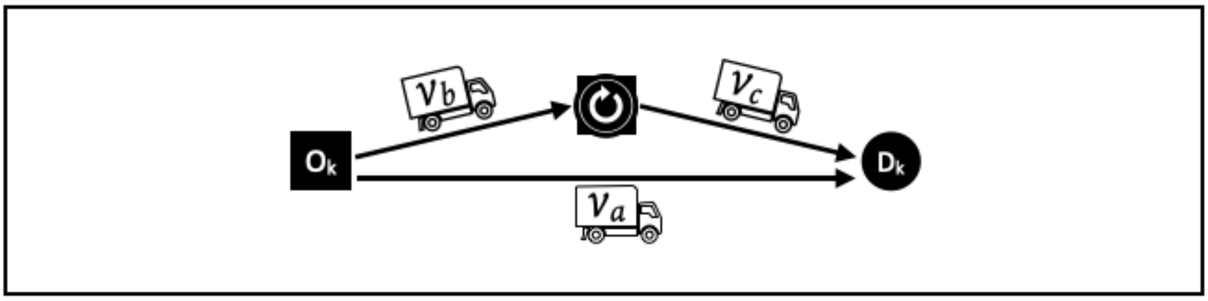


Figure 5: Illustration of straight delivery versus transshipment

The objective (11) minimizes the total distance covered, composed of loaded and empty trips. Unlike the PDP, loaded trips are no longer predefined but are also the subject of a decision thanks to network flow conservation constraint (12) that ensures each commodity k to be shipped from its origin to its destination, whether it is a straight delivery or via transshipments. To make sure that each request is satisfied, demand satisfaction constraint (13) guarantees every flows of commodity built in the network to be covered by any vehicle, thereby allowing a commodity to be served by several vehicles. To understand, Figure 5 shows that, while the PDP forces the journey from origin to destination using vehicle v_a, our SBPDP can also use v_b and v_c to ensure delivery, only provided that both vehicles pass through the same node in order to perform swap actions. Finally, routes are closed in regards to basic flow conservation constraints (14) and (15) ensuring that no truck gets stuck in a node, such that each vehicle ultimately gets back to its initial location. In the same time, constraint (16) restricts the length of the tours such that each truck respects its driving time limit, assuming the same handling time at each stop, whether it is to load, unload or swap its trailer.

3.6 Preprocessing algorithms

Regarding the driving time limit, it may happen that the length of a request is too long and remains unfeasible, even in a single round trip. In the following, we propose some preprocessing algorithms to handle those exceptions.

Too long trips need to be excluded from the optimization program since they will lead to an integer infeasible solution. To this end, the filtering algorithms documented in Appendix 1 have been implemented such that the variable $TooLong_{ij}$ can retrieve information about these particular transportation requests. Note that, depending on the model used (i.e. PDP or SBPDP), the definition of such routes varies.

Pickup and Delivery Problem

In a classical stay-with version of the PDP, a request is too long when it is impossible for a truck to cover the distance between origin and destination in a single return journey. Let $DistMax$ be the maximum distance between a distribution center and a customer such that :

$$DistMax = \left(\frac{Tmax}{2} - Thdl\right) * \ Speed$$

Based on this condition, Algorithm 1 documented in Appendix 1 identifies these particular trips in the PDP optimization program.

Swap-Body Pickup and Delivery Problem

In our SBPDP model, however, the definition of an unfeasible mission is less restrictive given that intermediate locations can be used by trucks to swap their cargo. Basically, even if the distance between an origin and its destination is greater than the admissible distance $DistMax$, it is still possible to transit the cargo through other nodes and share the request.

According to graph theory, a graph is connected if it exists at least one path from each node to each other node in the graph (Fouss et al., 2016). In our case, the length of that path should be lower or equal to $DistMax$. To put it simply, an infeasible trip in our SBPDP model only occurs when, considering a disconnected graph, the origin and destination are in two distinct sets of connected components.

We thereby assure that an origin is connected to its destination by checking if there is a shortest path between those two nodes such that each of the edges composing it is less or equal to $DistMax$. That condition is verified using a Boolean '*feasible'* in Dijkstra's algorithm as shown in Algorithm 2 documented in Appendix 1.

Forcing infeasible trips

Finally, to cope with these exceptions, Algorithm 3 documented in Appendix 1 authorizes overtime by offering the possibility of chartering specialized ships to respond to it with a single round-trip. As a result, excessively long missions are ensured by a simple back-and-forth shipment whilst excluding them from the optimization program. After all, they are taken into account in the computation of the MILP objective, thanks to the instantiation of $TooLong_{ij}$.

3.7 Limitations

Before we start presenting our computational experiments, we must acknowledge that our current SBPDP model presents several limits.

First, because subtour elimination constraints have not been included, it is likely that the impact of time pressure has been underestimated. Moreover, this unfortunately prevent us from drawing any conclusion regarding the number of trucks actually required.

Second, for two trucks to be able to swap their trailer, we should ensure not only that they pass through the same node, but also that this happen at the same time. Hence, we cannot guarantee good synchronization since the timings of the shipments are not taken into account. The corresponding durations of operations may be underestimated since we do not consider waiting times in situation where a driver reaches a swap location before its counterpart, for example.

Finally, we assumed an homogeneous fleet of vehicles so that connectivity and interoperability are taken for granted. However, the lack of industry standards described by Li et al. (2019) may lead to mismatch between trucks and trailers, in reality. Also, for the sake of security, not every site may be equally eligible to park a trailer.

As a result, it important to understand that our computational results provides the very best outcomes theoretically attainable with a swap-body implementation. Those are likely to be overestimated compared to what is practically achievable since we are unable to provide precise control for the operational process.

4. Computational experiments

In this section, we compare a classical stay-with version of the PDP with our SBPDP model, as described in Section 3.3 and 3.5 respectively. We first present our experimental settings and then present our computational results in details. Finally, we provide a decision support system that allows companies to assess the benefits that are likely to be generated through the development of swap locations, given their transportation requests configuration.

Note that manual efforts have been strongly reduced by automating the whole computational process, from data integration to visualizing the final results on a real map. The project architecture is documented in Appendix 2.

4.1 Experimental settings

To support our experiments, we use real instances of weekly travel data provided by a company active in the development of Fleet Management Systems. Unfortunately, due to strict confidentiality reasons, we are not able to report on the details of this collaboration.

We have eight different commodity matrices, each with around 20 transportation requests spread across 40 locations. Some locations may serve as points of origin or destination more than once, while others may only serve as transshipment points.

To allow for the main insights to appear clearly, it was preferable to investigate the problem with as few additional complication as possible by making several assumptions:

- Each truck runs at most one trailer at a time;
- All customers have unit demand expressed in Full Container Load ($\mathrm{R_k} = 1$);
- Distances as the crow flies are computed from the haversine formula and multiplied by a factor of 1.34 to estimate the actual road distance (Héran, 2009);
- The average speed is independent of the load ($Speed = 70 \text{ km/h}$);
- The handling time at all visited nodes is identical, whether it is to load, unload or exchange a trailer ($Thdl = 0.5$ h);
- The driving time constraint is an important parameter in our experiments as it limits the length of a tour, forcing trucks to use swap locations. To be able to compare the response of each model to time pressure variations, we chose eleven values of time constraints such that *Tmax* ranged from 30 to 80 hours, at 5 hours intervals.

Both the PDP and our SBPDP models have been implemented in Mosel using the LP and MILP solver of Xpress IVE (Version 1.24.10, 64 bits). All computations are conducted on Intel Core processor running at 3.2 GHz under Windows 10 with 8 GB of RAM. The limit solving time is set as 7200 seconds but computations stop whenever a minimum optimality gap of 0.5% is reached. The average optimality gap equals 2.3%.

4.2 Criterion for evaluation

In order to be able to compare the models, it is necessary to clearly define the criterion used in the evaluation process. To this end, we denote λ, the variation rate of distance in percentage such that:

$$\lambda = \frac{Optimal\ distance - Initial\ distance}{Initial\ distance}$$

where the *initial distance* is the single round-trip distance:

$$Initial\ distance = \sum_k R_k * \left(Dist_{O_k D_k}\right) + \sum_k R_k * \left(Dist_{D_k O_k}\right)$$

and the *optimal distance* is the value of our MILP objective:

$$Optimal\ distance = \sum_{i,j} x_{ij} * \left(Dist_{ij}\right) + \sum_{j,i} y_{ji} * (Dist_{ji})$$

Note that for clarity in our charts, the variation rates are displayed in absolute value. However when $\lambda < 0$ (i.e. initial distance > optimal distance) we speak of improvement rate. To put it simply, an improvement rate of 10% means that the distance traveled is reduced by 10% in the optimal solution, compared to the initial situation.

On the opposite, we speak of deterioration rate when $\lambda > 0$ (i.e. initial distance < optimal distance). To put it simply, a deterioration rate of 10% means that the optimal distance is increased by 10% compared to the initial situation. This may happen due to the detours needed to reach swap locations, as illustrated in Figure 1 where $c < h + g$.

Finally, our goal is to analyze the variation rates λ, comparatively for the PDP and our SBPDP.

	Initial situation	PDP		SBPDP	
One color per truck —— Loaded - - - - Empty					
Total distance	36842 km	34757 km	-5.6%	26801 km	-27.3%
Loaded trips (x)	18421 km	18421 km	+0%	18976 km	+3%
Empty trips (y)	18421 km	16335 km	-11.3%	7825 km	-57.5%

Table 1: Comparison between the PDP and the SBPDP regarding flows of operations and variation rates for a fixed driving time limit of 35 hours on a particular instance

4.3 Results overview

Before we break down our analysis into the driving time sensitivity study, we first give an overview of the benefits of swap actions on distance reduction, assuming a fixed weekly driving time limit of 35 hours per truck.

Operational example on a particular instance

In the following, we compare the optimization results for the PDP and our SBPDP on a particular instance. The set of transportation requests is documented in Appendix 3 and an illustration of the flow of operations for each model is provided in Table 1, with the corresponding distances and variation rates. In the initial situation, every commodities are ensured by single back-and-forth trips, which leads to a total distance of 36,842 kilometers to be traveled, half of whom are logically empty back-hauling trips. With a simple Pickup and Delivery model as described in Section 3.3, it is possible to design routes such that empty trips are reduced by 11.3%, which corresponds to a total improvement rate of 5.6%. Finally, the use of swap locations allows our SBPDP to reduce empty back-hauling trips by 57.5%. To achieve this, we must consent to an increase of 3% in loaded trips due to the 17 detours needed to reach the exchange points. In that specific example, our Swap-Body Pickup and Delivery model as described in Section 3.5 enables the total distance traveled to be reduced by 27.3%.

The number of detours is computed as the difference between the number of trips initially required and the number of flows actually built in the network. Intuitively, if we assume a transportation request between supplier A and customer B, such that initially:

$$\mathrm{k} \mid \mathrm{A} \rightarrow \mathrm{B} \mid R_k = 1$$

Then, a detour occurs when the commodity transits via swap location C, such that:

$$\mathrm{k} \mid \mathrm{A} \rightarrow \mathrm{C} \mid f_{\mathrm{ac}}^k = 1$$

$$\mathrm{k} \mid \mathrm{C} \rightarrow \mathrm{B} \mid f_{cb}^k = 1$$

Finally, the number of detours can be computed as follows:

$$\text{detours} = (f_{13}^k + f_{32}^k) - R_k = 1$$

$$= \sum_{i,j,k} f_{ij}^k - \sum_k R_k$$

Generalization of the results

For the sake of generality, every instances are solved under the same conditions so that results can be added together. The aggregated variation rates are presented in Table 2. On average, empty journeys are reduced twice more in our SBPDP (-50.04%) compared to a basic PDP (-25.92%). To achieve this, 13 trailer exchanges are generally needed, which increase the loaded trips by 2.35% because of detours to reach swap locations. Finally, the total distance to be covered is reduced by 23.84% with our SBPDP, compared to 12.96% with a classical PDP

Table 2: Aggregated results for the PDP and the SBPDP when assuming 35 hours driving time limit

		PDP	SBPDP
Total	Initial distance	205940 km	205940 km
	Optimal distance	179252 km	156841 km
	Variation rate	- 12,96 %	- 23,84 %
Loaded	Initial distance	102970 km	102970 km
	Optimal distance	102970 km	105393 km
	Variation rate	0 %	+ 2,35 %
Unloaded	Initial distance	102970 km	102970 km
	Optimal distance	76282 km	51447 km
	Variation rate	- 25,92 %	- 50,04 %
	Detours	0	13

However, this is what we obtain when assuming 35 hours before each truck returns to its starting point. In the next section, we propose further investigation on the impact of driving time limit variations.

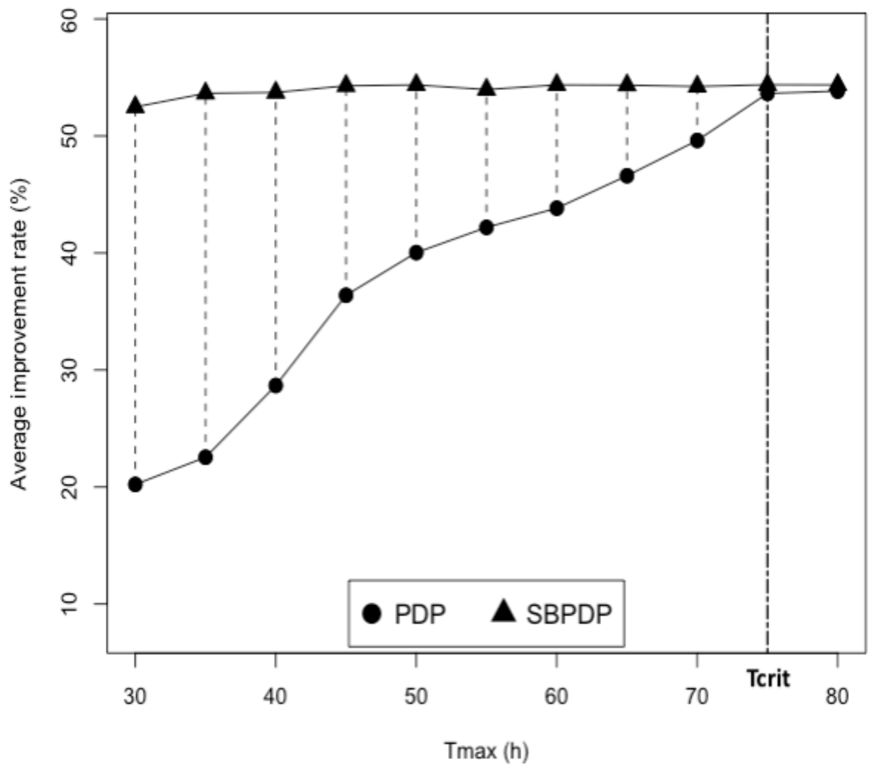
4.4 Driving time sensitivity analysis

In the following, we modify the driving time constraint gradually in order to analyze how each model reacts to time pressure variations. For computation time reasons, only four of the eight available instances are solved considering eleven different values for *Tmax*. By doing so, 88 experiments are conducted and optimization results are aggregated so that the average variation rates for every *Tmax* value can be reported. We first present the impact of driving time limit on empty trips reduction. Then we analyze the possible deterioration of loaded trips. Finally, we conclude on the total distance optimization.

Empty trips improvement

The impact of driving time limit on empty trips reduction is illustrated in Figure 6, comparatively for the PDP and our SBPDP. Note that, above a certain driving time limit, denoted *Tcrit*, both models are totally equivalent providing an average improvement rate of 54% in back-hauling trips, i.e. the distance traveled empty has more than halved. As expected, the use of swap locations appears to bring no real added value when time limit is not binding.

Figure 6: Average improvement rates on empty trips reduction for different driving time constraint configurations



However, under increasing time pressure (i.e. when *Tmax* decreases), there is a growing gap between the two models, such that driving time constraint quickly appears to be more restrictive in the PDP than in our SBPDP. To be accurate, calibration lines are calculated by linear regression such that the slope coefficients can be interpreted:

• In the PDP, driving time is observed to have a statistically significant reducing effect on distance optimization (p-value < 0.001). The improvement rate drops by 3.45 percentage points on average for every 5 hours lost. In other words, the PDP is very sensitive to driving time variations such that while an average empty trips reduction of 54% is possible when assuming a time limit of 75 hours, the improvement falls to 33% on average if a limit of 45 hours is imposed.

• In our SBPDP, driving time has no marginal effect on distance reduction as the slope is statistically insignificant at a materiality threshold of 50% (p-value > 0.5). To put it simply, enabling swap locations allows our model to maintain the lowest level of distance to be traveled without load. Under time pressure, trucks are now able to share the routes in such way that the driving time limit becomes less restrictive.

Finally, it has already been shown that our SBPDP is likely to increase the loaded trips due to the detours required to reach swap locations. Because the MILP objective assumes the same cost whether the vehicle is loaded or empty, it could be considered as a good trade-off to increase the loaded trips by 9% if it reduces the empty back-hauling trips by 10%, for instance. Obviously, this is not desirable in reality given the differences in fuel consumption, to name but one example. With this in mind, empty trips improvement cannot come at any price and we need to investigate the loaded trips deterioration as well.

Loaded trips deterioration

In the following, a clear relationship between the loaded trips variation and the number of detours needed to reach swap locations is established in order to give some more general insights on the response of our SBPDP to time pressure.

To this end, the left panel of Figure 7 illustrates the average number of detours for every *Tmax* configuration. As expected, the number of detours increases when driving time decreases. In fact, under the pressure of time, trucks are more and more pushed to share the routes, and therefore exchange their cargo in swap locations that are not necessarily located on their way.

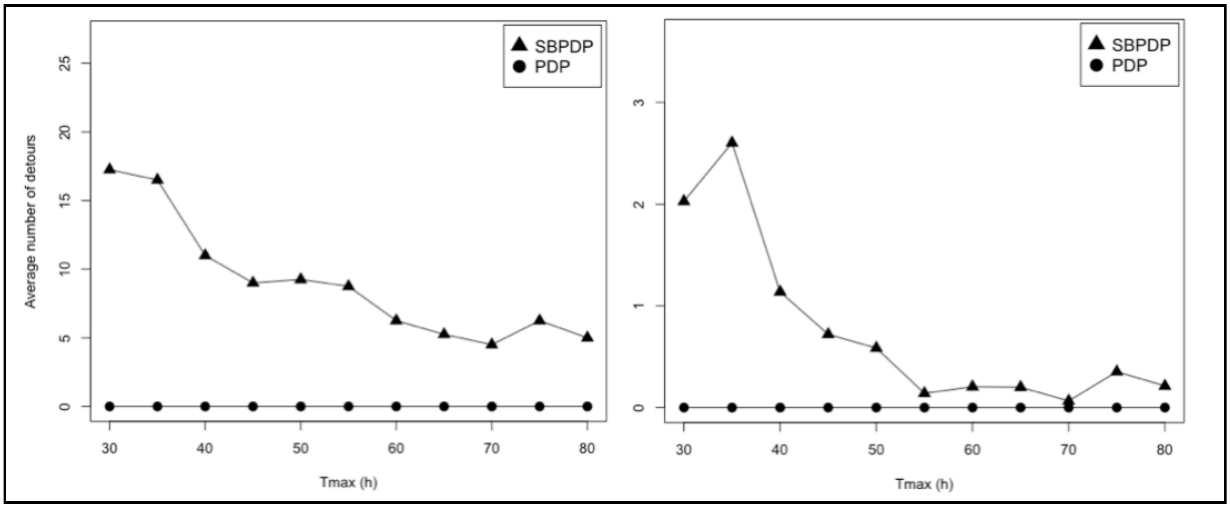


Figure 7: Relation between the driving time, the average number of detours and the average deterioration rate of loaded trips

Those deviations lead to an increase in the distance to be covered with load, as illustrated on the right panel of Figure 7, in which the corresponding average deterioration rates in loaded distance are displayed. For instance, a deterioration of 2% means that we have to travel 1.02 times the initial distance. A simple cross-analysis shows that each additional detour is observed to increase the loaded distance by 0.13%, on average.

Finally, we can clearly state that tighter time constraints force trucks to make detours in order to reach exchange points, which lead to a slight increase in the distance traveled with load.

Total distance variation

At first glance, the small losses caused by the increase in loaded trips seem to be largely compensated by the benefits brought by the reduction in empty trips. The overall impact of driving time constraint on total distance optimization is illustrated in the left side of Figure 8. Under a critical time limit denoted *Tcrit*, behaviors of each model is observed to differ substantially. While the basic PDP model can only passively accept the consequences caused by time pressure, our SBPDP model appears able to adapt to the conditions. By setting up swap locations, it splits the routes into an agile network, thereby maintaining improvement rate in total distance reduction at the highest level (i.e. $\lambda = -27\%$).

At this stage, we can already state that companies operating under time pressure should definitely set up swap locations. However, we still need to explain when a company is facing time pressure. In fact, because the limit of 75 hours is an average critical time computed from four different instances, it can not be regarded as a universal threshold.

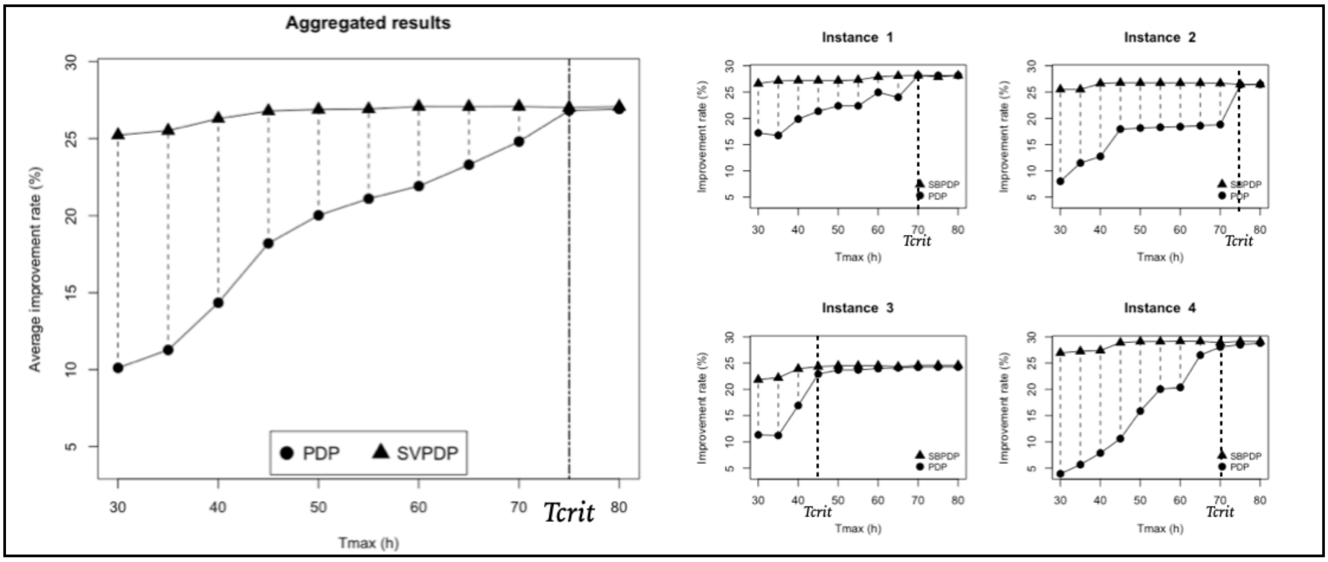


Figure 8: Improvement rates on total distance reduction for aggregated results and for each instance taken separately

Indeed, when we break down our analysis for every instances as illustrated in the right panel of Figure 8, we understand that this critical time is likely to vary sensibly depending on the transportation requests to be satisfied. For example, the real added value of our SBPDP only arises below a limit of 45 hours in the third instance, such that it would have been useless for that company to implement swap locations given a driving time constraint of 75 hours. Hence, time alone appears to be not sufficient to reveal the need of swap locations. In the following, we propose further investigation regarding time pressure definition.

Time pressure on transportation

Defining a critical pressure threshold turns out to be crucial since it informs us about the need to implement our model, or not. The pressure within a transportation request must be understood as a relationship between two parameters: the distance to be covered and the time available to do it, which is actually the definition of the speed itself:

$$Speed = \frac{Distance}{Time}$$

Such that a vehicle is in a rush if it has to travel a greater distance in a shorter period of time. Consequently, it must necessarily move faster or, considering a fixed average speed, several vehicles would be needed to ensure the delivery.

For example, let's assume a transportation request of 100 km return trip to be satisfied by a set of vehicles driving at 50 km/h, each of which can drive during one hour. Because they are twice as slow as they should, we would need two trucks to share the delivery equally. In that sense, the minimum number of trucks required to travel the initial round-trip distance is a good approach to estimate the pressure level in a transportation configuration:

$$Pressure\ level \cong \frac{Distance}{Speed * Time} = \frac{Distance\ to\ be\ covered}{DistMax\ per\ truck}$$

Such that the pressure increases if the distance increases, or if the time or speed decrease. Finally, we need to clarify what is meant by 'distance to be covered'. A first intuition would be to consider the total return-trip distance initially planned. However, this appears to be an incomplete approach as it does not account for the number of requests to be done. In fact, even if the total distance traveled remains the same, there is a difference between one thousand requests of ten kilometers and one request of ten thousand kilometers. In the first case, the driving time may not be binding and the PDP will surely be able to design routes efficiently. In the second, driving time will be more restrictive and swap locations will surely help to ensure the delivery. Given this, the weighted average distance per request is chosen and the pressure level can be stated as follows:

$$Pressure\ level = \frac{Average\ distance\ per\ request}{DistMax\ per\ truck}$$

$$= \frac{\sum_k Dist_{O_k D_k} * R_k}{k} \Big/ \left(\frac{Tmax}{2} - Thdl\right) * \ Speed$$

Such that:

- A pressure level close to 0 means that a typical request consumes only a few of available time. Therefore, it is easy to create interesting tours by combining requests.
- A pressure level close to 0.5 means that a typical request consumes half of available time. Therefore, it is hard to add other requests and swaps may be useful.
- A pressure level close to 1 means that a typical request consumes the whole available time. Therefore, it is impossible to add other requests and swaps become necessary.

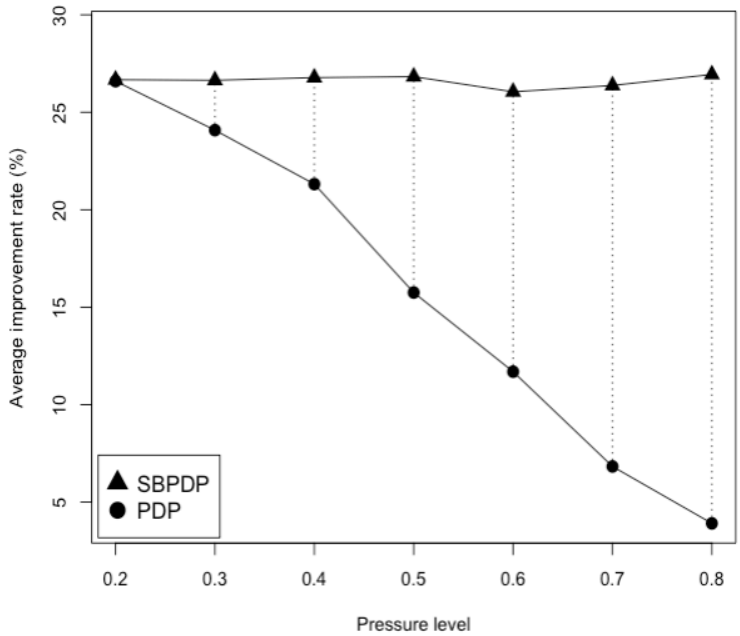


Figure 9: Impact of pressure level on total distance improvement rate

4.5 Decision support system

In the following, we propose to assess the additional benefits that are likely to result from the implementation of our SBPDP, in comparison with a classical stay-with version of the PDP, given the inherent pressure in a set of transportation requests.

For the sake of generality, pressure levels have been rounded to the first decimal for every instance and the corresponding average variation rates are displayed in Figure 9. Calibration lines are calculated by linear regression such that the slope coefficients can be interpreted:

• In our SBPDP, the pressure level is observed to have no statistically significant effect on total trips reduction, such that our model reduces the total distance by 26.92%, on average, in any situation.

$$|\lambda_{TTRP}| = 26.92\%$$

• In the PDP, however, the improvement rate decreases by 3.99 percentage points for every tenth additional level of pressure, and that impact is statistically very significant (p-value < 0.001).

$$|\lambda_{VRP}| = 36.03 - 39.91 * Pressure\ level$$

Note that the intercept has no real economic significance since a neutral pressure level implies that there are no missions to perform.

Given this, we can state that a company would find interesting to implement swap locations and use our SBPDP model only if it operates under a level of pressure such that, on average, a typical request consumes at least 23% of the driving time available:

$$|\lambda_{TTRP}| > |\lambda_{VRP}| \leftrightarrow \frac{Average\ distance\ per\ request}{DistMax\ per\ truck} > 0.23$$

Below that threshold, enabling swap locations would appear to be useless as the PDP provides the exact same outcomes as our SBPDP. Above that threshold, the gap between the two models will increase by approximately four percentage points for every additional tenth of pressure, in favor of our model.

Finally, the use of swap locations appears to be advantageous for company operating under increasing time pressure, i.e. when the driving time decreases or when the distance to be traveled increases. In a globalizing world economy, our approach could allow fleet managers to accept more distant missions and thus extend their area of operation, while maintaining a satisfactory level in cost reduction.

5. Conclusion

This paper analyzes the benefits for companies to set up swap locations in a Pickup and Delivery Problem. The conditions that influence these benefits are investigated to understand when our Swap-Body Pickup and Delivery approach is particularly profitable. For this, we propose a mixed integer programming model as a combination of a classical PDP formulation with a Network Design model.

We perform a total of 92 experiments using 8 real data set of weekly transportation requests from anonymized companies. The impact of time pressure on distance reduction is assessed by varying the driving time constraint parameters. It appears that the PDP is very sensitive to time pressure, causing deterioration in the empty trips reduction by 3.45 percentage points on average for every 5 hours lost. In contrast, our SBPDP is able to maintain a maximal level of improvement by reducing the empty trips by 54% in any situation.

To be able to provide a decision support system, we further investigate the time pressure on transportation through the relationship between the distance to be covered and the time available to do it. We show that our swap-body approach is of real interest when the return-trip for a request consumes at least 23% of the time available, on average. By doing so, we highlight the advantages of developing swap locations for companies operating under increasing time pressure, i.e. when the driving time decreases or when the distance to be traveled increases – two challenges posed by the extent of trade globalization.

This research could be extended in several directions. A first potential for improvement would be to consider the reduction in CO_2 emissions by considering different costs depending on whether a vehicle is loaded or empty. Also, it would be interesting to assume a heterogeneous fleet of vehicles to account for the lack of standards and interoperability. However, now that the potential savings regarding the use of swap locations are assessed, the natural next step could be also to look at delivery time windows in order to ensure good synchronization in operations.

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7. Appendices

Appendix 1: Preprocessing algorithms

Algorithm 1. Infeasible trips filtering in PDP.

for each *k* in S_K :
  if $Dist_{O_k D_k} > DistMax$:
    $TooLong_{O_k D_k} \coloneqq R_k$
  end-if

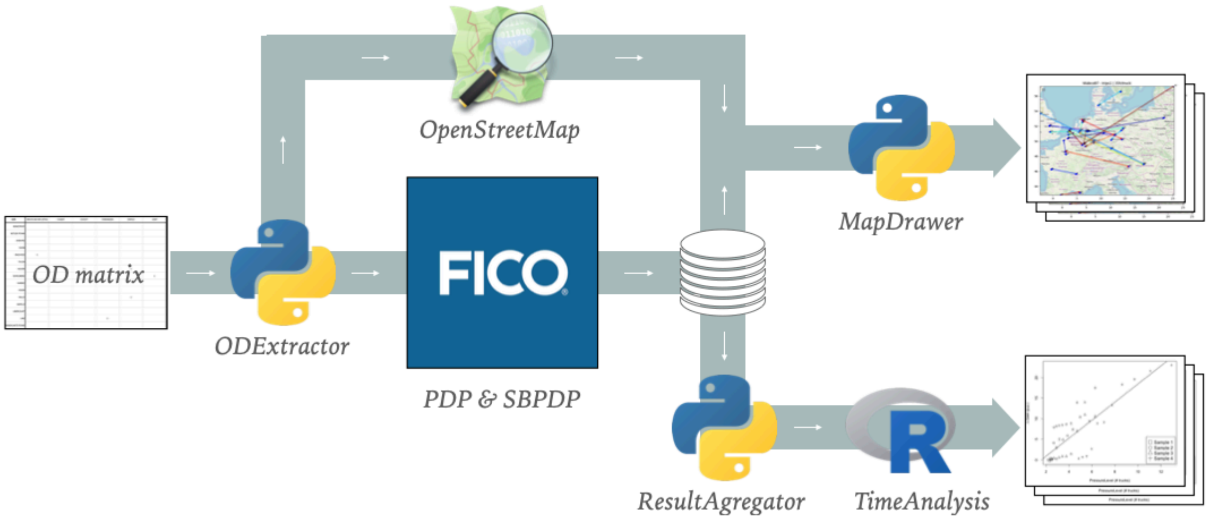
Algorithm 2. Infeasible trips filtering in SBPDP.

for each k in S_k | $Dist_{O_k D_k} > DistMax$:
  length(O_k) $\coloneqq 0$
  feasible(k) $\coloneqq False$
  for each *n* in S_N :
    length(*n*) $\coloneqq \infty$
    prev(*n*) $\coloneqq null$
  A=makequeue(S_N) using length-values as keys
  while *A* is not empty OR *b* ! $= D_k$:
    a = deletemin(*A*)
    for each *b* in S_N :
      if $Dist_{ab} > Dist_{max}$:
        decreaseKey(*A*,*b*):
      else if length(*b*) > length(*a*) + $Dist_{ab}$:
        length(*b*) = length(*a*) + $Dist_{ab}$
        prev(*b*) = *a*
        decreaseKey(*A*,*b*):
        if b == D_k:
          feasible(k) $\coloneqq True$
        end-if
      end-if
  end-while
  if feasible(k)== $False$:
    $TooLong_{O_k D_k} \coloneqq R_k$
  end-if

Algorithm 3. Infeasible trips removal.

for each k in S_k | $TooLong_{O_k D_k} > 0$:
  $x^{v*}_{O_k D_k} \coloneqq R_k$
  $y^{v*}_{D_k O_k} \coloneqq R_k$
  $R_k \coloneqq 0$

Appendix 2: Project architecture



Input: In our OD matrices, each row represents the name of the city of origin and each column the name of the city of destination.

ODExtractor.py: Based on city names, geographic coordinates are collected and the distances are computed with the Haversine formula create a square matrix of distance.

The second output is a commodity matrix where each row represents a request *k*, first column represents the origin O_k, second column the destination D_k and third column the size R_k.

The third output gives the limit values for geographic coordinates in order to define the boundaries of the map.

OpenStreetMap.com: A picture of a real map respecting the boundaries is captured.

FICO: Both models are solved using the commodity and the distance matrices as input. Optimization results and flow of operations are printed in CSV files stored in a bucket file.

MapDrawer.py: The flow of operations can be displayed on the map by selecting the instance to be solved, the model used, and finally tuning the parameter Tmax.

ResultAgregator.py: All the CSV files are collected from the bucket and results are aggregated into one table.

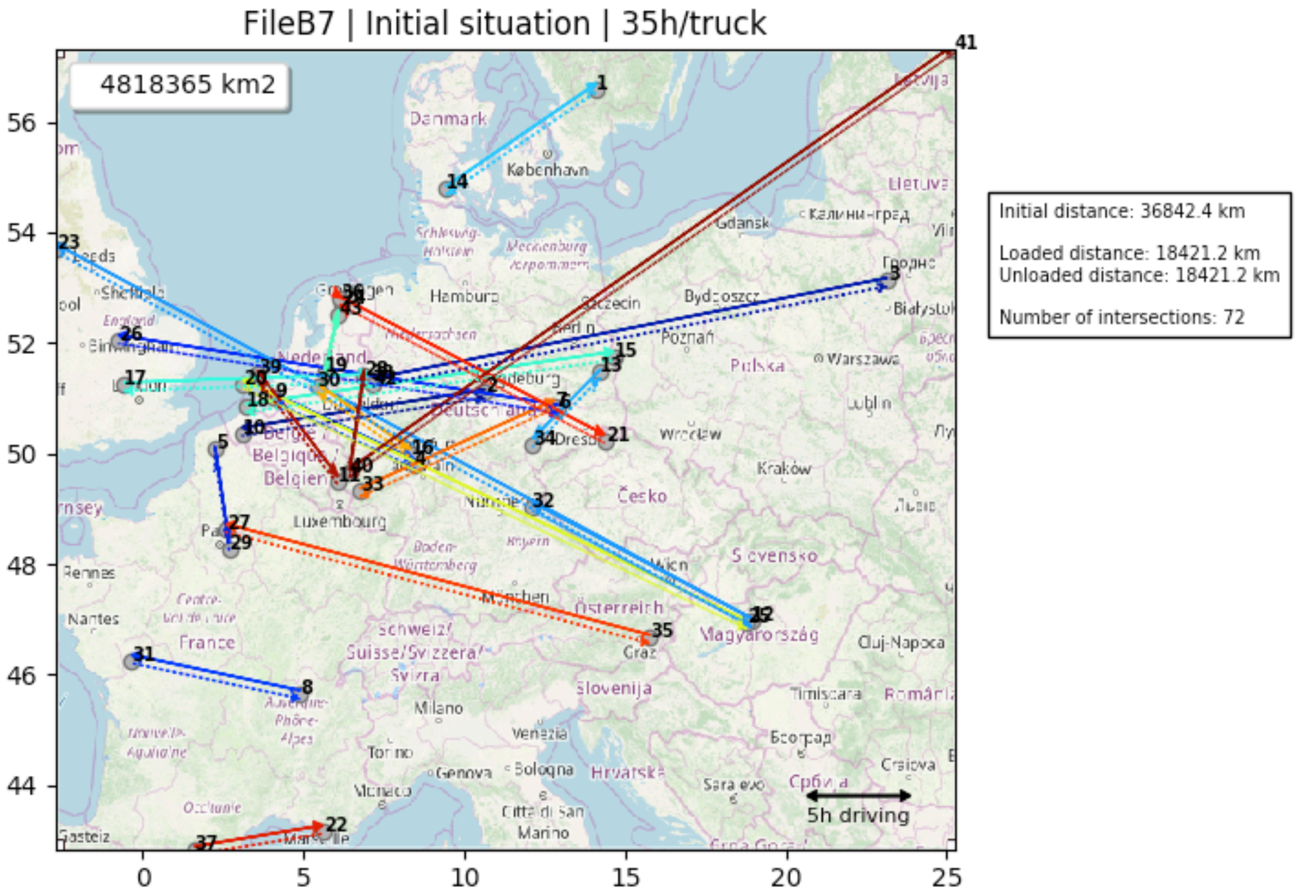
TimeAnalysis.r: Correlation analysis are coded using R and charts can be displayed.

Appendix 3: Transportation requests of a particular instance

FileB7

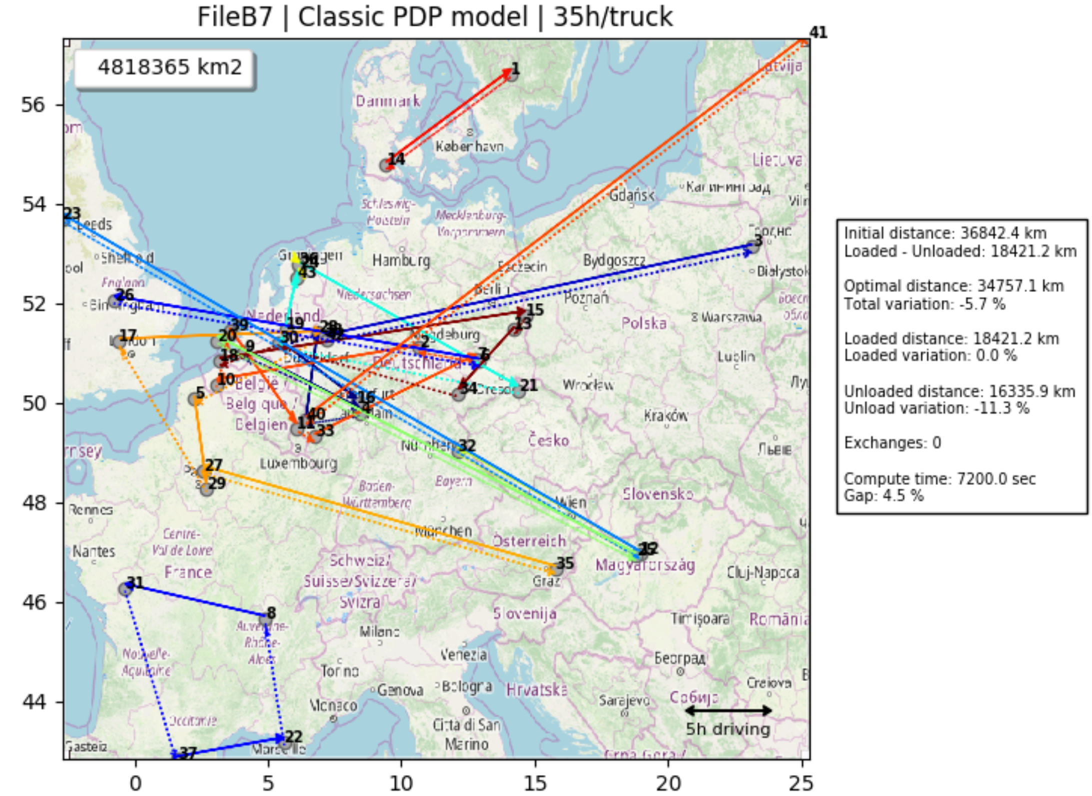
k	Origin	Destination	Quantity	Distance
1	BAD LANGENSALZA	DOUAI	1	721,84
2	BIALYSTOK	WUPPERTAL	1	1481,87
3	BONNEVILLE	NEMOURS	1	273,93
4	CHEMNITZ	MILTON KEYNES	1	1282,2
5	CORBAS	PRAHECQ	1	550,78
6	DENDERMONDE	BIEBESHEIM	1	453,79
7	DUNAUJVAROS	LEYLAND	1	2277,6
8	DUNAUJVAROS	REGENSBURG	1	747,55
9	ELSTERHEIDE	SELB	1	277,15
10	FLENSBURG	AELMHULT	1	477,15
11	GUILDFORD	VELBERT	1	709,89
12	GULLEGEM	FORST	1	1073,79
13	HELMOND	ZWOLLE	1	159,23
14	MEZOFALVA	HOUTAVE	1	1654,84
15	OVERPELT	GINSHEIM-GUSTAVSBURG	1	329,88
16	SAARLOUIS	CHEMNITZ ROEHRSDORF	1	623,37
17	SENTILJ	MOISSY CRAMAYEL	1	1352,87
18	STEENWIJK	KOZOMIN	1	853,34
19	STEENWIJK	MEPPEL	1	13,48
20	TARASCON	LA CIOTAT	1	438,62
21	VLISSINGEN	DUDELANGE	1	378,25
22	WELLEN	MUELHEIM	1	265,46
23	WELLEN	WENDEN	1	2010,45

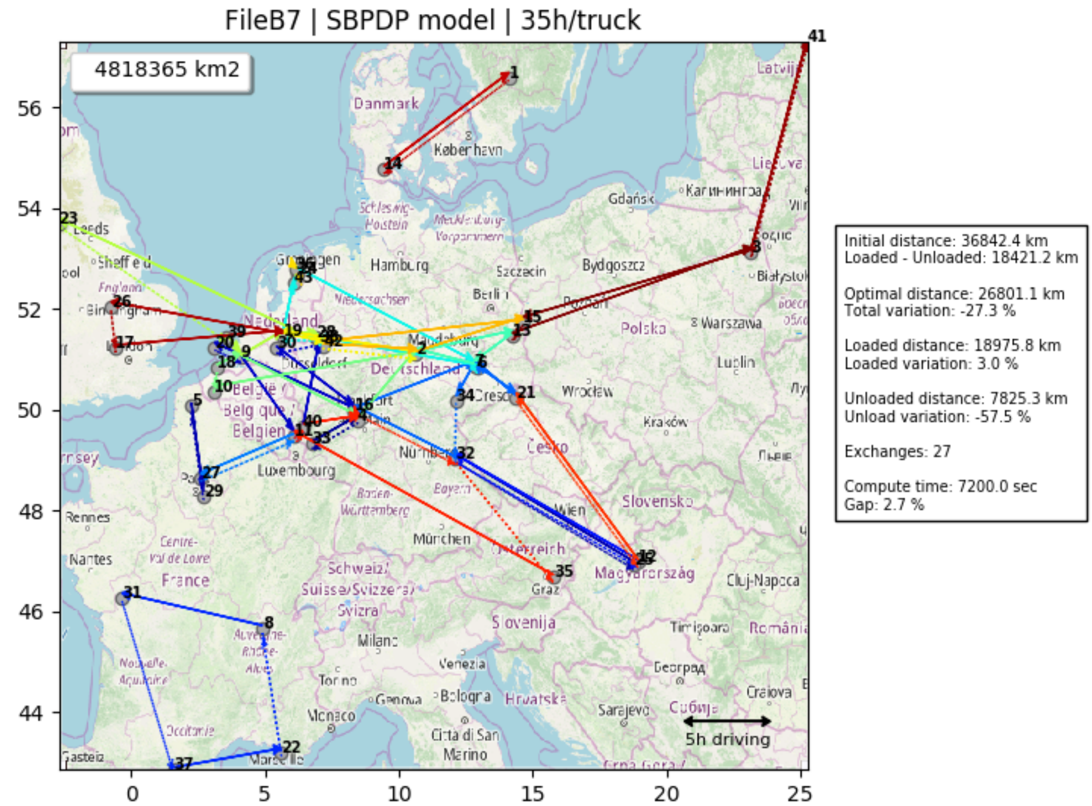
Appendix 4: Visualization of initial situation on a particular instance



- One color per truck
- Full line for loaded trips
- Dashed line for empty trips

Appendix 5: Comparison between PDP and SBPDP on a particular instance





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