D4.1 – Models and solution algorithms for finding robust solutions for the planning of synchromodal services

An overview of mathematical models and solution algorithms developed for the tactical planning of SAMSKIP's synchromodal services

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1 Executive summary

This deliverable outlines the mathematical models and solution algorithms developed to tackle the tactical planning phase of SAMSKIP's synchromodal services. In this phase, a planning must be made to deliver the forecasted customer demand from its origin to its destination on time. To this end, a specific route must be established for every forecasted customer order. This route can be either *direct*, utilizing a train service from the order's origin to its destination, or *indirect*, utilizing a train service to an intermediate location and then trucks from that intermediate location to the final destination. Indirect routing could be preferred for two reasons. First, routing a single train to a central location and using trucks thereafter could increase the train's utilization, thereby achieving better economies of scale compared to sending underutilized trains to multiple destinations. Second, ceteris paribus, indirect routing is more robust against delays because a smaller part of the train network is utilized. Our model considers several delay scenarios as inputs. One such delay scenario captures for each trip (i) whether a delay occurs and (ii) the delay amount, in case it occurs. A pertinent feature of our model is that it considers explicit customer requirements. Specifically, customers place orders that should be delivered until a required due date to a certain destination. In practice, customers appreciate that not all orders can be delivered on time, and set a target *service level*. For example, a 95% service level indicates that orders should be delivered by the due date in 95% of scenarios. Consequently, if a certain train track suffers from heavy delays, it may be better to reroute some orders to alternative destinations where there are less potential delays and thereafter use trucks to deliver the order to the end destination.

The problem we research is thus to route the customer orders from the origin to their destination and to decide which trains should be used for transporting the orders, so that the total routing and trucking costs are minimized on expectation. To gain insights on the solution structure, we draw a distinction between those cases where ample wagon capacity is available and cases where there exists only finite wagon capacity. This is very important because in the latter case delays of earlier trips may propagate on later trips, if not enough wagons exists at the origin. Therefore, managing the wagon inventory at the origin is an additional complexity captured by our second model, while the infinite capacity model can be thought of as its relaxation.

Both problems are formulated as Mixed Integer Linear Programming models which could be solved with a combination of exact and heuristic decomposition-based approaches.

Contents

2 Introduction

Transport companies have many different options for setting up a transportation network in order to deliver customer orders to their destination. Most networks focus on transporting cargo using a single mode, while a few companies utilize multiple transport modes to attain more cost-efficient deliveries. In the latter case, the network is termed a multimodal transportation network. The focus in this deliverable is on studying a multimodal network where trains depart from origin to multiple destinations and trucks can be used for end-to-end delivery.

The multimodal network of our focus is set up to schedule the delivery of forecasted customer orders from their origin to their destination. Train lines can be utilized to transport orders from any origin to a specific destination. Multiple train lines can be opened from a single origin, leading to the possibility to deliver orders from a single origin to multiple destinations. In our model, we focus on the single-origin multiple-destinations setting for two reasons. First, this setting is pertinent to SAMSKIP's operations, and therefore our models can be validated using real data from SAMSKIP. Second, it is usually the case that certain geographic areas are served by specific distribution centres, which keep their own wagon inventory. In such cases, the multi-origin problem is decomposable in a series of single-origin multiple-destination problems, such as the one we study here.

The design and management of multimodal operations requires planning at three different phases: the strategic, tactical and operational. Before explaining the important decisions taken in each phase, we first clarify some terms used throughout:

- A *train line* represents a railway connection between two stations (e.g. the train line Duisburg-Copenhagen)
- A *trip* represents the actual usage of a train line for a specific duration (e.g. a trip from Duisburg to Copenhagen and back at 08:00am, lasting 12 hours)
- A *train* represents the actual physical train that is used to perform a trip

Long-term decisions that reflect the wider goals and visions of a firm, such as infrastructure investments, are taken during the strategic planning phase. Specifically, one key decision is which train lines the firm wants to open during the subsequent years. This decision is taken by considering the importance of each market and how the company envisions their position therein. Due to budget restrictions, only a limited amount of train lines, the ones that are required to transport the expected customer orders, are operated. In case the company decides to make use of a certain train line, then they should also decide how frequently the line should be utilized during a year. This utilization frequency, denoted hereafter by f, represents the number of times the company wishes to use the chosen train line to deliver customer orders on an annual basis. Figure 1 gives an example of such a network with a single origin only. Four train lines are operated from this origin to four destinations. The train line (o-d1) has a frequency of 225, (o-d2) a frequency of 250, (o-d3) a frequency of 200, and (o-d4) a frequency of 210.

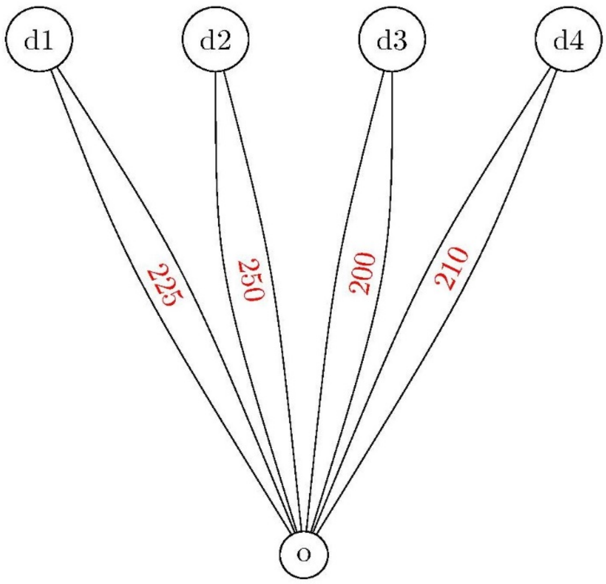

Figure 1: Example network

A second important decision taken in the strategic planning phase is to decide on the actual inventory of physical trains to keep at the origin. An actual physical train makes trips, which consist of a specific sequence of events: first all orders are loaded on the train (loading time ($t^{loading}$)), then the train travels to its destination (travel time (t^{travel})), there the orders are unloaded (unloading time ($t^{unloading}$)), after that the train travels back to the origin (t^{travel}). Thereafter, the train is ready to be deployed for a new trip, exhibiting the same sequence of operations, hereafter called a *cycle*. Note that we assume that the travel time of a train does not depend on the load on the train. Thus, the time to complete such a cycle (cycle time (t^{cycle})) can thus be calculated as:

$$t^{cycle} = t^{loading} + t^{travel} + t^{unloading} + t^{travel}$$
$$= t^{loading} + 2 * t^{travel} + t^{unloading}$$

If, for instance, the cycle time equals 47 hours, and the frequency requirement on this line is to have one train arriving at the destination per day, then we need at least two physical trains. It takes a train 47 hours before it is ready to start a new cycle, thus a train completes its cycle precisely one hour before it is required to start anew. Notice that if there are no additional wagons at the origin, a schedule like the one above is prone to delays, which cannot be absorbed by subsequent trips. The decision on the total number of physical trains stored at an origin is made during the strategic planning phase.

In the tactical planning phase decisions are taken on how to route the forecasted demand through the network eight weeks ahead of time. Specifically, these decisions are based on an estimation of the demand orders from customers and on the anticipated delays on the trips. Customer orders can be fully characterized by their size, origin, destination, release date and due date (specifying the latest possible arrival time for demand to be still on time at the customer). Orders are routed through the multimodal network from their origin to their destinations using the mode or modes of transport that are deemed more cost-efficient, and at the same time arrive at their destinations at or before their due dates. In our network, orders can only be delivered from the origin to a destination by making use of the railway network. However, orders can be delivered at *any* destination, not necessary the destination of the order. In that case, the orders with a different destination than where they are delivered need to be transported via truck to their actual destination. This inquires certain costs, but can be necessary in order to deliver on time.

The operational planning phase involves adjustments to the routing decisions taken in the tactical planning phase. The demand and delays are known at this stage, however there is not much flexibility to make changes, and therefore there is not much space for significant schedule alterations.

The focus of this deliverable is on the tactical planning phase. In this phase potential delays must already be taken into account. Potential delays have a large impact on the performance of the scheduling aspects during the tactical planning phase. Due to delays of trips orders may not be delivered on time leading to a low service level, which in time could have an impact on the firm's market share.

We consider two types of delays. First of all, during the tactical planning phase planned construction works must be taken into account. The railway operator performs construction works on railway tracks on a regular basis, leading to a very large delay when using the involved railway tracks. These types of delays can be taken into account in the travel time from origin to destination directly, because it is a constant factor during the whole planning horizon. Secondly, potential delays should already be considered when routing the customer orders. If a certain trip is likely to face a delay, then perhaps it is better not to use that trip and to route the orders via a different trip. These types of delays are taken into account by means of scenarios. A large variety of scenarios is used as input in the model, where each scenario represents a potential delay taking place on one (or more) track(s).

Trip delays not only have an influence on the service level of a customer, but, among other influences, also on the number of physical trains required. The number of trains scheduled to drive on a train line should be selected in such a way that it anticipates potential service disruptions. In other words, train scheduling should be robust to delays. In the previous example we had a train line with cycle time of 47 hours and only 2 trains are needed on this line in order to use the train line once a day. However, if there would have been a delay of 7 hours then it would no longer take 47, but 54 hours to complete the cycle. If there are only 2 trains, this translates to a 6-hour delay, and this delay will propagate to further days, as no action can be taken to absorb it. A robust solution would be to use 3 trains instead of 2, because in that case a relative small delay of one trip (less than 24 hours) has no effect on the departure time of the other trips. This needs to be taken into account when deciding to rent another physical train or not.

Two different models are created for the tactical planning phase. The first model is a simplification of reality, by assuming to have an infinite amount of physical trains present at the origin. The second model takes the actual amount of physical trains present at the origin into account. The first model is easier to solve and might give some insights in how to decompose the second model.

3 Literature review

Research in multimodal transportation is growing fast in the last few years and this trend is expected to continue. Several papers consider hub and terminal location problems or study specific routing requirements of orders through the network. Below we give a brief but coherent outline of the most notable research streams.

Hub location problems have received considerable attention in the multimodal literature. Racunica and Wynter (2005) use mathematical programming to find optimal locations of intermodal freight hubs. In Marufuzzaman et al. (2014) a model is proposed to find optimal locations for intermodal terminals and bio-refineries. Their model considers intermodal terminal disruptions, and its goal is to select the locations that minimize the joint establishment and transportation costs. It is notable that their model is deployed in the actual biofuel supply chain design of a practical application. Marufuzzaman and Eksioglu (2016) extended the work of Marufuzzaman et al. (2014) in order to cope with biomass supply fluctuations and to hedge against natural disasters. They create a dynamic multimodal transportation network design model which is solved using a Benders Decomposition approach and a rolling horizon. Although facility location decisions are not relevant for our model, we also capture delays that occurs while traversing network arcs, similar to the modelling of terminal disruptions.

Yamada et al. (2009) develop a bi-level network design model for investment planning in multimodal transportation. Their model decides which actions should be performed from a variety of possible actions, such as improving the existing infrastructure or investing in new roads, railways, sea links and/or freight terminals. The model is then solved using a heuristic approach based on a genetic local search algorithm. An et al (2015) addresses reliability issues for hub allocation problems. They develop hub-and-spoke networks that are reliable against disruptions. This is done by selecting back-up hubs and alternative routes next to selecting the hubs and routes which are used in the undisturbed situation.

An extensive literature review in papers that investigate the problems of finding locations for terminals can be found in Campbell and O'Kelly (2012).

There is also research done on the tactical planning phase of multimodal transportation. First of all, Zhang et al. (2015) incorporate the interaction between infrastructure and service in their models. Furthermore, they develop a multimodal route choice model that enables terminal choice which has been calibrated using transhipment data of intermodal terminals. They take CO2 pricing, terminal network configuration and hub-service networks into account as designing measures.

Meng et al. (2015) tackles the problem of delivering automobiles at its customers by automobile manufacturers. In their problem trains and ships can only deliver a few times a week, while trucks can deliver any time. They need to decide how much rail and water services the company must purchase for the delivery of the automobiles. They formulate the problem using a two-stage stochastic programming model and solve it using an improved sample average approximation procedure. Their model is tested on a case study from the Shanghai Automobile Industry, showing promising results.

Inghels et al. (2016) investigates whether it is useful for Municipal Solid Waste managers to shift from truck transport towards multimodal transportation. They use a dynamic tactical planning model which is solved using the state-of-the-art optimization software CPLEX. They apply their model to a real-life case study and show that multimodal transportation can compete with truck transportation.

Scheduling hazardous materials on a multimodal freight transportation network is investigated by Verma and Verter (2008), Verma and Verter (2010), and Verma et al. (2012). More specifically, all three papers consider rail-road multimodal transportation. Verma and Verter (2008) use a case study to understand the trade-offs existing in multimodal freight transportation networks for transporting hazardous materials. These insights are used in Verma and Verter (2010) to develop a model for planning the transportation of hazardous materials where there is only a single pair of multimodal terminals available. They take delivery times set by the customers into account for routing the hazardous materials. Their proposed model is solved using an iterative decomposition solution approach. In Verma et al. (2012), the work is extended to take multiple terminals into account. They use a bi-objective optimization model where both transport risk and transport costs are taken into account. A Meta heuristic solution framework is used to solve the problem.

There are also papers focussing on reliable transportation networks. Being able to recover from a disruption is an important indicator for the resilience of a network. Miller-Hooks et al. (2012) tries to measure and maximize the network resilience of intermodal freight transportation. Specifically, they try to determine the maximum resilience level of such a network and, at the same time, determine the best recovery actions to get to the maximum resilience level. They construct a two-stage stochastic program which is solved by an exact approach and with a Monte Carlo simulation. Chen and Miller-Hooks (2012) investigate the resilience of intermodal freight transportation networks. They define an indicator to quantify how well an intermodal network is able to respond to disruptions. A stochastic MIP is used for determining the resilience of the intermodal network and to identify which actions need to be taken just after the occurrence of the disruption. In order to solve the model, concepts from Benders Decomposition, Column Generation, and Monte Carlo simulation are used.

All the above models have similarities to our own, but do not capture the specificities as our problem at hand. An important difference of our model is that it takes customer service level, inventory of physical trains, and potential delay scenarios into account.

4 Infinite number of train wagons

This section introduces the model with an infinite number of physical wagons present at the origin, also called the Infinite Wagon Model (*IWM*). In section 3.1 the sets and parameters that are used in the model are explained. Thereafter a pre-processing model is presented in section 3.2 and the actual model is proposed in section 3.3.

4.1 Sets and Parameters

We introduce the set of trips T containing all possible trips which can be performed. Then, $T_d \in T$ contains all trips that have destination $d \in D$ as their destination. Furthermore, the list of customers that are expected to place customer orders for the week to schedule is denoted by C and the forecasted set of customer orders is denoted by O. The set $O_c \subseteq O$ denotes all forecasted orders made by customer $c \in C$. Finally, a list of possible delay scenarios is expressed by S. See Table XX for an overview of all the different sets used in the *IWM*.

Table 1: Sets

Set symbol	Description
D	Set of destinations
T	Set of trips
T_d	Set of trips with destination $d \in D$
C	Set of customers
O	Set of forecasted customer orders

O_c	Set of forecasted customer orders placed by customer $c \in C$
S	Set of delay scenarios

The problem at hand is to deliver customer orders from a central terminal to their destinations by train. Associate with a trip $t \in T$ are data represented by a tuple $\{st_t^d, st_t^a, \tau_t^d, \tau_t^{tt}, cap^r\}$, defined as follows. First, st_t^d is the departure station (origin), $st_t^a \in D$ the arrival station (destination), τ_t^d the departure time, τ_t^{tt} the total travel time of the trip, and cap^r the capacity available to transport orders on the trip. In this section, we assume that all trips have the same origin, namely the central terminal:

$$st_t^d = st_{t'}^d \ \forall\, t, t' \in T$$

Every order $o \in O$ can also be defined by a tuple $\{si_o, ds_o, rd_o, dd_o, cs_o\}$. Here, si_o defines the size of the customer order, $ds_o \in D$ is the location where the order needs to be delivered, rd_o is the date at which the order is placed, dd_o is the due date of the order, and $cs_o \in C$ represents the customer that placed the order.

A delay scenario $s \in S$ represents a potential delay scenario taking place on the network. To that end, $del_{s,t}$ defines the amount of delay on trip $t \in T$ under scenario s. Every customer $c \in C$ requires a service level sl_c. This service level demands that a customer order is delivered on time in at least sl_c number of scenarios. The total number of orders placed by a customer is denoted by $nr_c = |O_c|$.

As explained in the previous section, customer orders can be delivered to an intermediate destination. Thereafter, the order needs to be delivered to the end destination by truck. To this end, denote $tv_{d,d'}$ as the time it takes to travel from $d \in D$ to $d' \in D$ by truck. Furthermore, ts denotes the truck capacity, implying that, depending on the size of an order, a certain number of trucks is necessary to transfer it to its destination.

Our model captures a variety of costs that occur at different planning stages. Specifically, for every destination $d \in D$, a contract with respect to the yearly frequency f_d has been established. This means that the train line to destination $d \in D$ can be used f_d times a year against certain costs. In the tactical planning phase a schedule is made with respect to a single week only, but the decisions taken are influenced by f_d, i.e., the frequency level that has been established during the strategic phase. However, prorating the yearly frequency on a weekly basis may not be very accurate, especially in cases where the trip demand exhibits high variability across the year. To this end, we consider a weekly *frequency range*, given by a lower and upper bound (L_d and U_d) on the amount of times a trip to destination $d \in D$ can be used without disrupting over- or under-consuming the annual frequency f_d. The corresponding costs are δ^{less} for every trip used less than L_d, and δ^{more} for every trip used more than U_d to destination $d \in D$, capturing the impact of deviating from a forecasted schedule by a large number of trips. Finally, the costs of sending a truck from $d \in D$ to $d' \in D$ equals $\alpha_{d,d'}$.

4.2 Infinite Wagon Model

In order to decide which trips should be used, which should be cancelled, and how the forecasted customer demand should be routed to the correct destinations. First of all, the variable x_t represents whether trip $t \in T$ is used or cancelled, see Equation (3.1).

$$x_t = \begin{cases} 1 & if\ trip\ t \in T\ is\ used \\ 0 & if\ trip\ t \in T\ is\ cancelled \end{cases} \tag{3.1}$$

Next, a variable $y_{t,o}$ is used to route the customer demand through the network, as can be seen in Equation (3.2).

$$y_{t,o} = \begin{cases} 1 & if\ trip\ t \in T\ is\ used\ to\ transport\ customer\ order\ o \in O \\ 0 & otherwise \end{cases} \tag{3.2}$$

Another variable is used to route the customer orders from an intermediate train destination to its final destination by truck. Therefore, the variable $z_{t,o}$ is defined as in Equation (3.3).

$$z_{t,o} = \begin{cases} 1 & if\ a\ truck\ is\ used\ from\ st_t^a\ to\ ds_o\ just\ after\ trip\ t \in T \\ 0 & otherwise \end{cases} \tag{3.3}$$

Then, we can keep track of the amount of trucks required between two destinations just after a trip, with the variable $r_{t,d}$, see Equation (3.4).

$$r_{t,d} = Number\ of\ trucks\ send\ to\ destination\ d \in D\ just\ after\ trip\ t \in T \tag{3.4}$$

Furthermore, the variable $a_{o,s}$ is used to define the arrival time of an order during a certain delay scenarios, as shown in Equation (3.5).

$$a_{o,s} = Arrival\ time\ of\ order\ o \in O\ under\ delay\ scenario\ s \in S \tag{3.5}$$

A customer order can only be delivered too late under a limited number of scenarios, depending on the service level required by the corresponding customer. Therefore, we need a binary variable stating whether a customer order is delivered too late under a scenario or not, see Equation (3.6).

$$t_{o,s} = \begin{cases} 1 & if\ order\ o \in O\ is\ delivered\ too\ late\ under\ delay\ scenario\ s \in S \\ 0 & otherwise \end{cases} \tag{3.6}$$

Finally, the variable c_d^l is used to measure the negative deviation from the lower bound L_d and the variable $c_d^m$is used to measure the positive deviation from the upper bound U_d, see Equations (3.7) and (3.8).

$$c_d^l = \begin{cases} L_d - \sum_{t \in T} x_t, & if\ \sum_{t \in T} x_t < L_d \\ 0 & otherwise \end{cases} \tag{3.7}$$

$$c_d^m = \begin{cases} \sum_{t \in T} x_t - U_d, & if \ \sum_{t \in T} x_t > U_d \\ 0 & otherwise \end{cases} \tag{3.8}$$

With these variables and parameters we can define the IWM as:

$$\min \sum_{d \in \mathcal{D}} (c_d^l \cdot \delta^{less} + c_d^m \cdot \delta^{more}) + \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} r_{t,d} \cdot \alpha_{st_t^a, d} \tag{3.9}$$

subject to:

$$\sum_{t \in \mathcal{T}} y_{t,o} = 1 \qquad \forall o \in \mathcal{O} \tag{3.10}$$

$$x_t \geq y_{t,o} \qquad \forall o \in \mathcal{O}, t \in \mathcal{T} \tag{3.11}$$

$$y_{t,o} - z_{t,o} = 0 \qquad \forall o \in \mathcal{O}, t \in \mathcal{T} : st_t^a \neq ds_o \tag{3.12}$$

$$\sum_{o \in \mathcal{O}} y_{t,o} \cdot si_o \leq cap^t \cdot x_t \qquad \forall t \in \mathcal{T} \tag{3.13}$$

$$\sum_{\substack{o \in O \\ ds_o = d}} y_{t,o} \cdot si_o \leq r_{t,d} \cdot cap^t \qquad \forall t \in \mathcal{T}, d \in D : d \neq st_t^a \tag{3.14}$$

$$y_{t,o} = 0 \qquad \forall o \in \mathcal{O}, t \in \mathcal{T} : \tau_t^d < rd_o \tag{3.15}$$

$$a_{o,s} = \sum_{t \in \mathcal{T}} (y_{t,o}(\tau_t^d + \tau_t^{tt} + tr_{s,t}) + z_{t,o} tv_{st_t^a, ds_o}) \qquad \forall o \in \mathcal{O}, s \in \mathcal{S} \tag{3.16}$$

$$a_{o,s} \leq dd_o + t_{o,s} \cdot M \qquad \forall o \in \mathcal{O}, s \in \mathcal{S} \tag{3.17}$$

$$\sum_{o \in \mathcal{O}_c} \sum_{s \in \mathcal{S}} t_{o,s} \leq nr_c - sl_c \qquad \forall c \in \mathcal{C} \tag{3.18}$$

$$c_d^l \geq L_d - \sum_{t \in \mathcal{T}_d} x_t \qquad \forall d \in \mathcal{D} \tag{3.19}$$

$$c_d^m \geq \sum_{t \in \mathcal{T}_d} x_t - U_d \qquad \forall d \in \mathcal{D} \tag{3.20}$$

The objective function, Equation (3.9), minimizes the total costs. The first part of the costs reflect to the costs of using the trips and the second part for sending a truck to resolve deliveries to the wrong destination.

The constraints that need to be satisfied are the following. First of all, Constraints (3.10) state that every order needs to be transported from the central terminal to *one* of the destinations. Constraints (3.11) makes sure that a trip is used when customer orders are routed over that trip. Furthermore, orders have to be delivered to their correct destination one way or another. Therefore, Constraints (3.12) states that if orders are transported to an intermediate destination, then they need to be transported by truck to the correct destination afterwards.

Every trip has only limited capacity to transport customer orders. Therefore, Constraints (3.13) state that the total size of customer orders transported on a trip may not exceed the capacity of the trip. Trucks also have sparse capacity for transporting customer orders. Consequently, Constraints (3.14) define the total number of trucks required to deliver orders that have just arrived from a trip on the intermediate destination to their end destination.

A customer order can only be transported via a trip after its release date, this is modelled by Constraints (3.15). Then, every customer order arrives at their destination at a specific time. Constraints (3.16) defines exactly this arrival time of a customer order. The arrival time is a sum of the departure time of the used trip, plus its travel time from the origin to the destination of the trip, plus, if this destination is not the destination of the order, the time it takes to transport the order to its destination by truck. A customer order must be delivered before its due date in order to be on time. Constraints (3.17) defines the variable ($t_{o,s}$) stating whether a customer order is transported on time under a certain scenario or not. Using that variable, Constraints (3.18) state that the number of scenarios in which customer orders are late may not exceed the maximum number as defined by each customer service level.

Finally, Constraints (3.19) and (3.20) are used to set the variables c_d^l and c_d^m correctly. Note that the variables must always be greater or equal to 0, thus these constraints are sufficient to define the variables correctly.

4.3 Alternative IWM

The IWM in the previous section can be formulated more efficiently with respect to constraints (3.16)-(3.18). To that end, we introduce a parameter $I_{t,o,s}$ that equals 1 if order $o \in O$ arrives too late at its destination when it is transported via trip $t \in T$ under scenario $s \in S$ and 0 otherwise. Algorithm 1 shows how to initialize this parameter. First of all, the algorithm initializes the parameter $J_{t,o}$ to 1 if the destination of trip $t \in T$ differs from the destination of order $o \in O$. Next, the algorithm checks whether the order is delivered too late when using trip t under scenario s, taking into account a possible transfer by truck afterwards.

Algorithm 1 An algorithm to initialize the parameter $I_{t,o,s}$

for Order $o \in \mathcal{O}$ **do**
    for Trip $t \in \mathcal{T}$ **do**
        Initialize parameter $J_{t,o}$
        if $st_t^d == ds_o$ **then**
            $J_{t,o} = 0$
        else
            $J_{t,o} = 1$
        end if
        for Scenario $s \in \mathcal{S}$ **do**
            if $\tau_t^d + \tau_t^{tt} + tr_{t,s} + J_{t,o} \cdot tv_{st_t^a, ds_0} > dd_o$ **then**
                $I_{t,o,s} = 1$
            else
                $I_{t,s,o} = 0$
            end if
        end for
    end for
end for

Having computed the indicator parameter $I_{t,s,o}$ we can replace Constraints (3.16) – (3.18) by the following constraint:

$$\sum_{o \in O_c} \sum_{s \in S} \sum_{t \in T} I_{t,s,o} \cdot y_{t,o} \leq nr_c - nc_c \cdot sl_c \;\; \forall c \in C$$

This constraint states that at most $nr_c - nr_c \cdot sl_c$ orders of customer $c \in C$ may be deliverd too late. Thus, $sl_c\%$ of the orders are delivered on time.

5 Finite number of train wagons

The model in the previous section assumes a sufficiently large number of physical train wagons present at the origin. However, in practice there are situations where limited wagon capacity is an issue that should be taken into consideration. Obviously, a trip can only depart if there is at least one physical train wagon present at the origin. Otherwise, the trip is either delayed until a wagon is present or the trip is cancelled. In this section a model is described that assumes a limited number of physical train wagons at the origin and where the delay is modelled through a list of potential departure times for a trip.

The model introduced in this section is an extension of the model in the previous section. Therefore, the same parameters and variables that are used in the previous section, are now used again. However, modelling the interaction of departure times requires a number of additional parameters and variables required as well. First, parameter inv describes the number of physical train wagons present at the origin at the start of the planning period. So, inv represents the start inventory. Secondly, θ represents the costs for hiring an additional physical train wagon for the remainder of the planning period, which in our context is one week.

The first important difference with the IWM is that we can reroute orders to trips on a scenario by scenario basis. Due to delays and a limited amount of inventory, it may be inevitable to change the routing solutions with respect to the scenario without any delays. Consequently, the decision on which trip an order is transported is made per scenario. However, it is not possible to decide just per trip per scenario whether to cancel the trip or not. Once a trip is cancelled in the base scenario (the scenario without any delays, denoted by s_0), the same trip must be cancelled in *all* other scenarios as well. Note that the trips that are used in the base scenario may get cancelled in other scenarios against π costs per additional cancellation in a scenario. The delays on a trip during a scenario can propagate to other trips, because it takes longer before a physical wagon has returned to the origin in case of delays. Consequently, if there are no remaining train wagons present at the origin, the coming trip is either cancelled, or delayed in order to wait for a physical train wagon to become available. In most railway settings, it is not possible to for a freight train to depart at an arbitrary time, as passenger trains usually take priority over freight trains. It is thus usually the case that freight trains only have certain time slots on which they can depart. This situation is modelled by means of a list of potential departure times for each trip. If the first time slot is not feasible, because there is no inventory available for the trip to depart, then the train is delayed until the next time slot. We refer to this model as *Delay List Model* (*DLM*). DLM takes different departing times for a trip into account in order to model the potential delays when there is lack of inventory.

The set of trips T, set of orders O, set of scenarios S, set of destinations D, and set of customers C are also used in the *DLM*. Furthermore, a new set Φ is added, containing all possible time slots on which trips can depart. Then, the set $O_c \subseteq O$ contains all orders placed by customer $c \in C$. Finally, the set $\Phi_t \subseteq \Phi$ contains all possible time slots on which trip $t \in T$ can depart.

In order to keep track of the inventory at the origin, a parameter describing the time it takes for a train wagon to travel back from its destination to the origin under a certain scenario is required: $\tau_{t,s}^{b}$. This travel time can differ per scenario, depending on potential delays within a scenario.

The parameter τ_ϕ denotes the time belonging to time slot $\phi \in \Phi$. Secondly, the tuple $\{\tau_t^d \in \Phi, \tau_t^{tt}, st_t, cap_r\}$ is used for trip $t \in T$. Here, τ_t^d denotes the first possible departure time slot of trip t; $\tau_t^d = \{\phi \in \Phi_t : \tau_\phi \leq \tau_{\phi'} \ \forall \ \phi' \in \Phi_t\}$. Next to that, τ_t^{tt} denotes the travel time without delays for trip t, st_t defines the destination station of the trip, and cap^r the total capacity available on the trip. Then, order $o \in O$ has data associate with the following tuple: $\{ds_o, rd_o, dd_o, si_o\}$. Here, ds_o is the destination of order o, rd_o defines the release date of order o, i.e., the date on which the order is placed by the customer. Furthermore, dd_o and si_o denote the order due date and size respectively. These parameters are the same as in the *IWM*. With respect to orders and trips, two additional sets are introduced to ease the *DLM* notation:

$$T_o^1 \subseteq T: ds_o = st_t$$
$$T_o^2 \subseteq T: \tau_t^d \geq rd_o$$

The base scenario s_0 is the scenario where no delays take place on any of the trips. Thus, all other scenarios describe a potential delay scenario. To this end, the parameter $tr_{t,s}$ defines the delay taking place on trip $t \in T$ under scenario $s \in S$. Consequently, the total travel time from origin to destination of trip $t \in T$ under scenario $s \in S$ equals $\tau_t^{tt} + tr_{s,t}$.

The lower and upper bound on the number of trips going to a destination are defined by L_d and U_d. As before, the total number of orders placed by customer $c \in C$ is defined by nr_c. Furthermore, all customers demand to have a service level sl_c, defined as the percentage of orders that should be delivered on time.

The capacity of a truck is defined by cap^t, thus every truck is assumed to have the same capacity for orders. The total travel time for a truck to travel from destination $d \in D$ to $d' \in D$ is defined by $tv_{d,d'}$.

A new parameter $I_{t,o,s,\phi}$ is introduced in (4.1), showing if order o is delivered on time under scenario s, when allocated to trip t and time slot ϕ. This parameter has similarities with $I_{t,o,s}$ as introduced in Algorithm 1. Therefore, a similar Algorithm is used to set $I_{t,o,s,\phi}$, see Algorithm 2.

$$I_{t,o,s,\phi} = \begin{cases} 1, & if\ order\ o \in O\ is\ delivered\ too\ late\ when\ using\ trip\ t \in T \\ & under\ scenario\ s \in S\ while\ departing\ at\ timeslot\ \phi \in \Phi_t \\ 0, & otherwise \end{cases} \quad (4.1)$$

Algorithm 2 An algorithm to initialize the parameter $I_{t,o,s,\phi}$

```
for Order o ∈ O do
    for Trip t ∈ T do
        Initialize parameter J_{t,o}
        if st_t^d == ds_o then
            J_{t,o} = 0
        else
            J_{t,o} = 1
        end if
        for Scenario s ∈ S do
            for Time slot φ ∈ Φ_t do
                if τ_φ^d + τ_t^{tt} + tr_{t,s} + J_{t,o} · tv_{st_t^a,ds0} > dd_o then
                    I_{t,o,s,φ} = 1
                else
                    I_{t,s,o,φ} = 0
                end if
            end for
        end for
    end for
end for
```

Finally, the parameter $b_{t,s,\phi,\phi'}$ is used to describe whether trip $t \in T$, departing at timeslot $\phi \in \Phi_t$ is back at the origin under scenario $s \in S$ before the timeslot $\phi' \in \Phi$ takes place:

$$b_{t,s,\phi,\phi'} = \begin{cases} 1, & if\ \tau_\phi + \tau_t^{tt} + tr_{t,s} + \tau_{t,s}^b > \tau_{\phi'} \\ 0, & otherwise \end{cases}$$

The costs used in the *DLM* are defined similar as before, except for the extra costs θ representing the costs for hiring one additional physical train wagon and the costs β for cancelling a trip under a scenario when it is not cancelled in the base scenario.
All costs used in the *DLM* can be summarized as:

δ^{less}	The costs per negative deviation from L_d
δ^{more}	The costs per negative deviation from U_d
$\alpha_{d,d'}$	The costs of sending a single truck from $d \in D$ to $d' \in D$
θ	Costs of hiring one additional physical train wagon
β	Costs for cancelling a trip under a scenario when the trip is not cancelled in the base scenario

In total, nine different families of decision variables are used in the *DLM*, as defined in (4.2) – (4.10). First, $x_{t,s,\phi}$ denotes whether a trip departs at a time slot under a certain scenario. See equation (4.2).

$$x_{t,s,\phi} = \begin{cases} 1, \ if\ trip\ t \in T\ is\ used\ under\ scenario\ s \in S\ at\ timeslot\ \phi \in \Phi_t \\ 0, \ otherwise \end{cases} \tag{4.2}$$

Secondly, $y_{t,o,s,\phi}$ defines whether an order is transported via a trip at a certain timeslot under a scenario or not, see Equation (4.3).

$$y_{t,o,s,\phi} = \begin{cases} 1, \ if\ order\ o \in O\ is\ transported\ by\ trip\ t \in T \\ \qquad at\ timeslot\ \phi \in \Phi_t\ under\ scenario\ s \in S \\ 0, \ otherwise \end{cases} \tag{4.3}$$

The variable $z_{t,o,s}$ defines whether a truck is used after a trip to transfer an order to its end destination under a scenario or not, see Equation (4.4).

$$z_{t,o,s} = \begin{cases} 1, \ if\ a\ truck\ is\ used\ to\ transported\ order\ o \in O\ from\ station \\ \qquad st_t\ to\ station\ ds_o\ under\ scenario\ s \in S \\ 0, \ otherwise \end{cases} \tag{4.4}$$

Then, $r_{t,d,s}$ denotes the total amount of trucks required to deliver orders to a certain destination just after a trip under a certain scenario. The more orders with a different destination than the destination of the trip transported on it, the larger the variable $r_{t,d,s}$ will be, see (4.5).

$$r_{t,d,s} = The\ amount\ of\ trucks\ sent\ to\ destination\ d \in D \\ just\ after\ trip\ t \in T\ under\ scenario\ s \in S \tag{4.5}$$

The variable η_t defines the total deviation from the base scenario for a trip. A deviation is defined as cancelling a trip, while the trip was not cancelled in the base scenario. Thus every cancelled trip under a scenario is a deviation if the trip is not cancelled in the base scenario.

$$\eta_t = The\ total\ number\ of\ scenarios\ deviation\ from \\ the\ base\ scenario\ s_0\ for\ trip\ t \in T \tag{4.6}$$

Next, $c^l_{d,s}$ is used to measure the negative deviation from the lower bound under a scenario and the variable $c^m_{d,s}$ is used to measure the positive deviation from the upper bound under a scenario, see (4.7) and (4.8).

$$c^l_{d,s} = \begin{cases} L_d - \sum_{t \in T} \sum_{\phi \in \Phi_t} x_{t,s,\phi}, & if\ \sum_{t \in T} \sum_{\phi \in \Phi_t} x_{t,s,\phi} < L_d \\ 0, & otherwise \end{cases} \tag{4.7}$$

$$c^m_{d,s} = \begin{cases} \sum_{t\in T}\sum_{\phi\in\Phi_t} x_{t,s,\phi} - U_d, & if\ \sum_{t\in T}\sum_{\phi\in\Phi_t} x_{t,s,\phi} > U_d \\ 0, & otherwise \end{cases} \tag{4.8}$$

Then, $i_{\phi,s}$ is used to keep track of the inventory just after a time slot under a scenario, see Equation (4.9).

$$i_{\phi,s} = The\ inventory\ at\ the\ origin\ just\ after\ time\ slot\ \phi \in \Phi \text{ under scenario s} \in \text{S} \tag{4.9}$$

Finally, ω is used to define the number of additional hired physical wagons.

$$\omega = Number\ of\ additional\ hired\ physical\ train\ wagons \tag{4.10}$$

With the above sets, parameters, and variables, the model can be defined as follows:

$$\min \sum_{d\in\mathcal{D}}\sum_{s\in\mathcal{S}}(c^l_{d,s}\cdot\delta^{less} + c^m_{d,s}\cdot\delta^{more}) + \sum_{t\in\mathcal{T}}\sum_{d\in\mathcal{D}} r_{t,d}\cdot\alpha_{st^a_t,d}) + \sum_{t\in\mathcal{T}}\eta_t\cdot\beta + \omega\cdot\theta \tag{4.11}$$

Subject to:

$$\sum_{t\in\mathcal{T}^2_o}\sum_{\phi\in\Phi_t} y_{t,o,s,\phi} = 1 \qquad \forall o\in\mathcal{O}, s\in\mathcal{S} \tag{4.12}$$

$$\sum_{\phi\in\Phi_t} y_{t,o,s,\phi} - z_{t,o,s} = 0 \qquad \forall o\in\mathcal{O}, t\in\overline{\mathcal{T}_o}, s\in\mathcal{S} \tag{4.13}$$

$$x_{t,s,\phi} \geq y_{t,o,s,\phi} \qquad \forall t\in\mathcal{T}, \phi\in\Phi_t, s\in\mathcal{S} \tag{4.14}$$

$$\eta_t = \sum_{s\in\int}\sum \phi\in\Phi_t(x_{t,s_0,\phi} - x_{t,s,\phi}) \qquad \forall t\in\mathcal{T} \tag{4.15}$$

$$\sum_{\phi\in\Phi_t}(x_{t,s_o,\phi} - x_{t,s,\phi}) \geq 0 \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{4.16}$$

$$\sum_{o\in\mathcal{O}}\sum_{\phi\in\Phi_t} y_{t,o,s,\phi}\cdot si_o \leq cap^r \cdot \sum_{\phi\in\Phi_t} x_{t,s,\phi} \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{4.17}$$

$$\sum_{\substack{o\in\mathcal{O}\\ ds_o=d}}\sum_{\phi\in\Phi_t} y_{t,o,s,\phi}\cdot si_o \leq cap^t \cdot r_{t,d,s} \qquad \forall o\in\mathcal{O}, t\in\overline{\mathcal{T}^1_o}, s\in\mathcal{S} \tag{4.18}$$

$$\sum_{o\in\mathcal{O}_c}\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}}\sum_{\phi\in\Phi_t} y_{t,o,s,\phi} I_{t,o,s,\phi} \leq nr_c - sl_c \qquad \forall c\in\mathcal{C} \tag{4.19}$$

$$i_{\phi,s} = inv + \omega + \sum_{t\in\mathcal{T}}\sum_{\phi'\in\Phi_t} x_{t,s,\phi'}\cdot b_{t,s,\phi',\phi} - \sum_{t\in\mathcal{T}}\sum_{\substack{\phi'\in\Phi_t\\ \tau_{\phi'}\leq\tau_\phi}} x_{t,s,\phi'} \qquad \forall\phi\in\Phi, s\in\mathcal{S} \tag{4.20}$$

$$c^l_{d,s} \geq L_d - \sum_{t\in\mathcal{T}_d}\sum_{\phi\in\Phi_t} x_{t,s,\phi} \qquad \forall d\in\mathcal{D}, s\in\mathcal{S} \tag{4.21}$$

$$c^m_{d,s} \geq \sum_{t\in\mathcal{T}_d}\sum_{\phi\in\Phi_t} x_{t,s,\phi} - U_d \qquad \forall d\in\mathcal{D}, s\in\mathcal{S} \tag{4.22}$$

The objective function (4.11) consists of four parts. The first part minimizes the deviations from the lower and upper bound of the number of trips. The second part minimizes the total truck costs, the third part the number of deviations from the base scenario, and the final part minimizes the number of additional hired train wagons.

Constraints (4.12) are used to ensure that all orders are transported by train to a destination. Orders can only be transported after the order is placed, thus after its release date. This is also ensured by Constraints (4.12). If an order is transported to a different destination than where the order needs to be delivered, then a truck must be used after the trip in order to locate the order to its end destination, as modelled by Constraints (4.13). Furthermore, if a trip is used to transport an order at a timeslot, then that trip must depart from that specific time slot, as modelled by Constraints (4.14).

Constraints (4.15) measures the total deviation from the base scenario η_t. This deviation is the total number of trips that get cancelled in a scenario, while the trip is not cancelled in the base scenario. It is not possible to use a trip in a scenario when it was already cancelled in the base scenario, this is modelled by Constraints (4.16).

Furthermore, Constraints (4.17) and (4.18) are used to set the capacity on a trip and the capacities within a truck. First, Constraint (4.17) states that the total size of the orders transported on a trip may not exceed the capacity on that trip. Then, Constraint (4.18) state that the amount of trucks used to transport orders just after a trip to a different destination depend on the total order size that needs to be transported.

Constraints (4.19) set the service level per customer. The service level defines the maximum number of scenarios in which an order can be delivered too late, this number may not be exceeded.

Then, Constraints (4.20) is used to keep track of the inventory just after a time slot. This inventory may never be negative, otherwise there are not enough physical train wagons present.

Finally, Constraints (4.21) and (4.22) are used to set the deviations from the lower and upper bound on the number of trips. This is done in a similar way as before.

6 Solution Methods

Solving the *DLM* is challenging from a computational viewpoint, and while the *IWM* is much easier to solve, it still requires considerable computational effort. However, solutions to the *IWM* may not practical since they do not capture the propagation of delays to upcoming trips. To exploit the solvability of *IWM* onto solving the *DLM*, we propose a solution technique where the *IWM* solution is used as input to solve the *DLM*, as described in Figure 2.

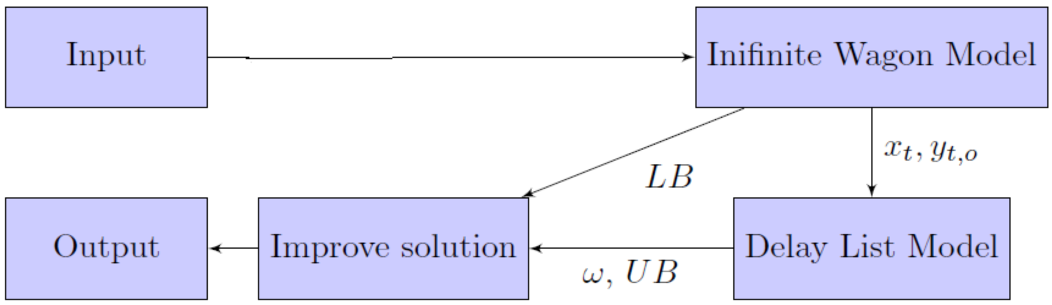

Figure 1. Solution strategy for the DLM.

First, the *IWM* is solved to (near) optimality. By using the *IWM* solution, the trips that are used, and the routing of the orders, can then be fixed in the *DLM*. The *DLM* has then only the flexibility to decide on which time slots the trips should depart and how many additional train wagons are required in order to find the solution.

Solving the *DLM* with fixed trips and fixed orders on trips has, among others, as output the amount of additional train wagons required to produce the same solution as the *IWM*. If zero additional train wagons are required, then the optimal solution has been found for the *DLM*. Otherwise, there might exist a different routing where less additional train wagons are required. Note that the optimal solution to the *IWM* gives a lower bound to the optimal solution of *DLM*, because the train wagons are not taken into account. Furthermore, the solution to the fixed *DLM* gives an upper bound to the optimal solution, because there was no flexibility in deciding which trips to use.

Three different heuristics are used to improve the solution in case one or more additional wagon is required after solving the fixed *DLM*. All three heuristics are based on iteratively fixing a part of the solution to the *DLM* and then solving the remaining part. Therefore, all three heuristics are called semi-fixed *DLM* heuristics.

Scenario Based Heuristic (SBH), Trip Based Normal Heuristic (TBNH), and Trip Based Wagon Heuristic (TBWH).

The first semi-fixed *DLM* heuristic to tackle the problem is the *Scenario Based Heuristic* (*SBH*). For this algorithm, a slightly modified version of the *DLM* model is required. A new variable ω_s is used to determine the amount of extra hired additional wagons per scenario. Then, Constraints (4.20) are replaced by the two constraints (5.1) and (5.2), indicating that the actual wagon inventory should be at least at much as it is required by each scenario. The inventory per scenario is now based on ω_s instead of ω, as shown in (5.1). Furthermore, the overall additional number of wagons required is the maximum value of ω_s; $\omega = max_{s \in S}\, \omega_s$, as modelled by (5.2).

$$i_{\phi,s} = inv + \omega_s + \sum_{t\in T}\sum_{\phi\in\Phi_t} x_{t,s,\phi}\cdot b_{t,s,\phi',\phi} - \sum_{t\in T}\sum_{\substack{\phi'\in\Phi_t \\ \tau_{\phi'}\le\tau_\phi}} x_{t,s,\phi'} \quad \forall\phi\in\Phi, s\in S \tag{5.1}$$

$$\omega \geq \omega_s \quad \forall s \in S \tag{5.2}$$

Then, the SBH is introduced in Algorithm 3.

Algorithm 3 SBH

```
1: Solve IWM to get x_t and y_{t,o}
2: Solve the fixed DLM to obtain ω_s and ω
3: if ω = 0 then
4:     The found solution is optimal.
5: else
6:     S* = {s|s = arg max ω_s}
7:     while |S *| < |S| * ϵ do
8:         Add flexibility to x_{t,s,ϕ} and y_{t,o,s,ϕ} for all scenarios s ∈ S*
9:         Solve semi fixed DLM
10:        S* = {s|s = arg max ω_s}
11:    end while
12:    The found solution is the improved solution
13: end if
```

In line 1 the *IWM* is solved in order to obtain the values of x and y such that the trips used and the orders on trips are fixed in the *DLM*. Here, the trips perform in the IWM are also perform in the DLM in every scenario and the orders to trip allocation in the IWM is the same in every scenario of the DLM. Note, however, that the time slot for a used trip is still flexible. This fixed version of the *DLM* is solved in line 2, in order to obtain the values of ω_s and ω. If ω equals 0, it means that 0 additional train wagons are required to solve the problem. Consequently, the IWM solution, which is a DLM relation, is feasible for the DLM, and therefore optimal. Otherwise, the solution might be improved by lowering the number of additional train wagons required. In that case, we first determine which scenarios are the bottleneck in line 6. If the number of bottleneck scenarios is greater than a certain percentage ϵ of all scenarios we terminate, because reducing ω can have a large impact on cost, as it influences many scenarios. Otherwise, flexibility in terms of cancelling and rerouting orders is given to all scenarios $s \in S^*$, see line 8, and the *DLM* model is now solved while fixing all trips and routing variables in all scenarios except for the scenarios $s \in S^*$. After solving the semi fixed DLM, the set S^* is determined again and the while loop starts over again.

The second semi-fixed *DLM* heuristic is the *Trip Based Normal Heuristic* (*TBNH*). For this heuristic no additional variables or constraints are necessary. While in the *SBH* some scenarios are fixed, while others can be changed, *TBNH* fixes or leaves flexibility to trips instead. A trip is either fixed in all scenarios, or flexible in all scenarios. Only the trip allocation variables are fixed (x), as the trip allocation variables (y) are not fixed in any iteration. The complete algorithm is proposed in Algorithm 4.

Algorithm 4 TBNH

1: Solve IWM to get x_t and $y_{t,o}$
2: Solve the fixed DLM to obtain ω
3: **if** $\omega = 0$ **then**
4:     The solution of the fixed DLM is optimal.
5: **else**
6:     NrIterations = 0
7:     bestSolution = solution of fixed DLM
8:     **while** $\omega > 0$ and NrIterations < MaxNrIterations **do**
9:         **for** Trip $t \in T$ **do**
10:             Decide with 90% probabilty to fix trip t
11:         **end for**
12:         Solve semi fixed DLM to obtain new ω
13:         **if** Solution semi fixed DLM < bestSolution **then**
14:             bestSolution = Solution semi fixed DLM
15:         **end if**
16:         NrIterations++
17:     **end while**
18:     bestSolution is the final solution to the algorithm
19: **end if**

The first two lines are the same as before, in line 1 the *IWM* is solved in order to obtain the values of x and y to fix the variables for the fixed *DLM* that is solved in line 2. If $\omega = 0$, it means that the optimal solution to the problem is found and we can stop (see line 3). Otherwise, we need to keep track of the number of iterations and of the best found solution so far (see lines 6 and 7). As long as $\omega \neq 0$ and we have not reached the maximum number of iterations, randomly approximately 90% of the trips are fixed in line 10. The semi-fixed *DLM* is then solved to obtain a new ω and a new solution. If this solution is better than the one found before, it is stored in line 14. After the while loop, the best found solution is returned.

The third, and final, semi-fixed DLM heuristic is the *Trip Based Wagon Heuristic* (*TBWH*). This heuristic is very similar to the *TBNW*, only a different objective function is used throughout the while loop. The most important part of the objective function of the *DLM* is the amount of additional train wagons required. In the TBWH the focus is on finding solutions with as little additional train wagons required as possible, thus the objective function only penalizes this part. All other parts of the objective function are neglected at first. See Algorithm 5 for the complete heuristic.

Algorithm 5 TBWH

1: Solve IWM to get x_t and $y_{t,o}$
2: Solve the fixed DLM to obtain ω
3: **if** $\omega = 0$ **then**
4: The solution of the fixed DLM is optimal.
5: **else**
6: NrIterations = 0
7: bestSolution = solution of fixed DLM
8: **while** $\omega > 0$ and NrIterations < MaxNrIterations **do**
9: **for** Trip $t \in T$ **do**
10: Decide with 90% probabilty to fix trip t
11: **end for**
12: Solve semi fixed DLM where the objective is only to minimize ω, to obtain a new ω
13: **if** Solution semi fixed DLM < bestSolution **then**
14: bestSolution = Solution semi fixed DLM
15: **end if**
16: NrIterations++
17: **end while**
18: Fix x and y and solve the fixed DLM to obtain the best solution
19: **end if**

As can be seen, only lines 12 and 18 differ from *TBNH*. In line 12 the semi-fixed *DLM* is solved where only the amount of additional train wagons are minimized, all other parts of the objective are neglected. After the while loop is finished a solution has been found that minimizes the amount of train wagons required only, but a solution must be found with respect to all objective coefficients. Therefore, the fixed *DLM* is solved once again in line 18, where the x and y variables of the best solution found are fixed. Note that the fixed *DLM* has flexibility to decide the timeslot on which a used trip departs.

In conclusion, the *SBH* has flexibility on scenario level, while both the *TBNH* and the *TBWH* have flexibility on trip level, where the focus of the *TBWH* is on minimizing the amount of additional train wagons only. The performance of the three heuristics will be compared to each other in the results section.

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