Loading tow trains ergonomically for just-in-time part supply

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Abstract

Faced with an aging workforce, many manufacturing companies consider alleviating the ergonomic strain of material handling on their workers increasingly important. This is one of the reasons why frequent small-lot deliveries of parts to the assembly stations on the shop floor via small electric delivery vehicles – so-called tow trains – have become widespread in many industries. Deploying tow trains, however, does not automatically ease the ergonomic burden on logistics workers, but requires careful stowage planning in addition. In this paper, we consider the following problem. Given a set of bins of differing weight to be carried by tow train to a given set of stations on the shop floor, where should each bin be stowed on the tow train such that it can be unloaded efficiently from an economic perspective while also minimizing the ergonomic strain during loading and unloading? We investigate the physiological stress of handling bins on different levels of a tow train wagon by applying an established ergonomic evaluation method from the human factors engineering literature. We model the ensuing optimization problem as a special type of assignment problem and propose suitable exact and heuristic solution methods. In a computational study, our approaches are shown to perform well, delivering optimal solutions for instances of realistic size within fractions of a second in many cases. We show that optimal stowage plans can significantly ease the physiological burden on the workforce without compromising economic efficiency. We also derive some insights into the ideal layout of the tow train from an ergonomics perspective.

\textit{Keywords:} assignment; tow trains; ergonomics; generalized assignment problem; part feeding

1. Introduction

In many industries, feeding parts from a warehouse to the assembly lines such that neither transport frequencies nor line-side inventories are excessive has become a major problem. This is due to, on the one hand, an extreme
product variety (that results from the customization of mass products), and, on the other hand, very limited space on the shopfloor, which prohibits large inventories and intense shopfloor traffic. Taking parts in large lots (e.g., entire pallets) straight to the assembly line via industrial truck has therefore become highly unattractive for many companies (e.g., Medbo, 2003, Boysen et al., 2015). Instead, tow train systems are often used. Tow trains consist of a small electric towing vehicle attached to a handful of wagons, as depicted in Figure 1. Some few tow trains operate as automated guided vehicles with minimal human intervention, although most tow trains are still operated by a driver (Golz et al., 2012, Emde and Gendreau, 2017, Lieb et al., 2017). More often than not, in addition to driving the train, its operator is also responsible for loading the tow train at a central warehouse or a just-in-time “supermarket” and unloading it at the assembly line. An intersectoral study by Lieb et al. (2017) found that the tow train driver is responsible for loading the tow train in 63% and for unloading the tow train in 89% of the cases.

Tow trains have a higher transport capacity than forklifts, allowing frequent small-lot deliveries of parts to multiple stations in one tour. Parts are typically pre-sorted and packed into small standard-size bins and delivered just-in-time, such that workers at the assembly line need not waste any time searching for or unpacking parts. One central advantage of this type of part feeding system is that it is supposed to make it easier for workers to handle parts in an ergonomic manner (e.g., Neumann and Medbo, 2010, Emde and Boysen, 2012b, Battini et al., 2013). It is obviously less stressful from an ergonomics perspective to handle small bins than entire pallets (Neumann and Medbo, 2010). This aspect is becoming increasingly important as many manufacturers struggle with an aging workforce (e.g., Otto and Scholl, 2011, Aiyar et al., 2017, European Commission, 2017).

![Figure 1: Tow train without load](http://www.ssi-schaefer.ua/uploads/pics/071_routenzug_02.jpg)

Tow trains do not automatically make logistics processes more ergonomic, however. Specifically, the tow trains still need to be loaded at the depot and unloaded at the stations by human workers. This requires lifting and setting down many individual bins of differing weight. Although tow train wagons are often designed as gravity flow racks, such that bins inserted at one end of the wagon slide to the front by themselves, not all tiers of a wagon can be accessed with the same ease. Typically, from an ergonomics perspective, the middle level of a rack is the least stressful to (un-)load (Petersen et al., 2005). Reaching overhead or bending down causes more strain (see Section 5.1.2 for more details).

This study is motivated by a problem we encountered at the main production facility of a major German machine manufacturer. This company supplies its assembly lines from a central warehouse via a fleet of ten tow trains, attached to wagons equipped with gravity flow racks. Parts are picked just-in-time in multiple

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1The picture “Routenzuglösung” belongs to SSI Schäfer and was downloaded from [http://www.ssi-schaefer.ua/uploads/pics/071_routenzug_02.jpg](http://www.ssi-schaefer.ua/uploads/pics/071_routenzug_02.jpg). SSI Schäfer permitted the usage of this content in the context of this paper.
order picking stations from pallets and crates into standardized bins destined for specific workstations at the assembly line. The pickers place the finished bins onto an automated sortation conveyor, which funnels them to the correct tow train to be loaded by the operator. Once equipped, the tow train sets off on a milk run through the production facility on one of multiple fixed routes. The whole system is computerized, meaning that the pickers know which parts to pick when for which station, the sortation conveyor knows where to send which bin, and the tow train operators know when the tow train visits which stations on what route. All bin movements onto and from the tow train are logged via a barcode scanner. Material, once requested, can be shipped to final assembly within two to four hours. While the company is quite satisfied with the responsiveness and efficiency of the system, the ergonomic stress caused by (un-)loading heavy bins has so far been taken into account only in a rudimentary manner.

To the best of our knowledge, until now, optimization and planning models regarding situations like the one described above have only considered time and cost as objectives (for a more detailed review see Section 2). In this context, this paper makes the following contributions. First, we investigate the physiological stress of handling bins on different levels of a tow train wagon by applying an established ergonomic evaluation method from the human factors engineering literature to the loading and unloading of tow trains we observed in practice. Second, we formulate, analyze, and solve the optimization problem of how to stow bins on a tow train such that they are readily accessible in the right order during unloading and such that the total ergonomic strain on the workforce is minimized during both loading and unloading. Third, in a series of computational experiments we show the efficacy of our solution approaches and demonstrate that incorporating ergonomic objectives into tow train (un-)loading greatly eases everyday part feeding. We also derive some recommendations as to how to operate tow trains ergonomically.

2. Literature review

Although just-in-time in-house logistics is quite a new topic in scientific research, various issues concerning the logistics of tow trains and, on a more general level, in-plant part feeding, have received attention in recent years. Problems that companies operating tow trains usually encounter range from planning the optimal location of in-plant logistics areas (“supermarkets”) on a strategic level, to operational problems such as the routing, scheduling, and loading of tow trains (Emde and Boysen, 2012a). Holistic approaches are developed by Choi and Lee (2002) and Golz et al. (2012), who consider tour planning, scheduling and loading simultaneously and provide heuristic solution procedures for these problems. An overview of in-house milk run problems is provided by Alnahhal et al. (2014), while Battini et al. (2013) and Boysen et al. (2015) give an overview of the supermarket concept specifically in the automotive industry, where it is the most common.

The supermarket location problem is discussed by Battini et al. (2010), Emde and Boysen (2012a) as well as Alnahhal and Noche (2015). These authors consider the objective of optimally placing supermarkets on the shop floor, such that assembly line stations are supplied at minimal total cost, where the costs consist of fixed expenditures for erecting additional supermarkets and distance-dependent tow train travel costs.

Vaidyanathan et al. (1999) and Emde and Schneider (2018) deal with the problem of routing tow trains. The objective considered in these papers is to minimize the weighted sum of tow trains in use as well as line-side stocks that need to be held at workstations to satisfy demands in-between tow train re-visits, with the latter depending on the processing time of the planned tow train routes.

Tow train scheduling is considered by Emde and Boysen (2012b), Fathi et al. (2016) as well as Emde and Gendreau (2017). Following the concept of lean production, the problem, as regarded by these authors, consists of deciding when to execute which tow train tour such that line-side demands are fulfilled and line-side stocks
are minimized.

Finally, Emde et al. (2012) consider the problem of loading tow trains with the objective of minimizing line-side stocks.

Our brief review of the literature shows that research on just-in-time in-house logistics, and especially on tow train operations, has recently gained momentum. Ergonomic aspects have, however, not yet been investigated in this context, despite the high amount of manual human work that is still associated with the loading and unloading of tow trains in practice today (see Lieb et al., 2017). The handling of heavy loads that may be associated with the (un-)loading of tow trains exposes the tow train drivers to an increased injury risk that the company may mitigate by taking account of ergonomic measures in planning tow train operations. We note that Boysen et al. (2015) already highlighted a few years ago that taking account of ergonomic aspects in decision support models for material handling is an important research gap that requires further investigation.

While ergonomic aspects have not been considered in the planning of tow train operations, there is a substantial amount of research in the human factors engineering literature that investigates the manual handling of materials on worker health and safety. In this stream of research, manual material handling (MMH) activities, such as the ones encountered in (un-)loading tow trains, have been shown to increase the workers’ risk of developing muscular-skeletal disorders (MSD) (see e.g., Punnett and Wegman, 2004, Larsson et al., 2007, Roquelaure et al., 2009). Some researchers estimate that between 50% and 75% of all MSD cases are directly related to MMH activities (Lavender et al., 2012). In the EU, MSD are assumed to account for up to 58% of all work-related illnesses, amounting to an estimated annual cost of 2% of the gross national product in the European Union (Schneider and Irastorza, 2010).

In the context of order picking, which shares some similarities with the (un-)loading of tow trains with respect to the MMH activities involved (but not with respect to the managerial characteristics of the decision problem), the increased risk of developing MSD has been confirmed in various field studies (Braam et al., 1996, Gardner et al., 1999, Garg, 2000, Marras et al., 2010, Lavender et al., 2012). Even though the increased risk of developing MSD from MMH activities (and hence order picking) is undisputed in the literature, Neumann and Medbo (2010), Grosse et al. (2015) as well as Grosse et al. (2017) point out that ergonomic aspects have scarcely been considered in decision support models for such activities, and that much work remains to be done. A few notable exceptions are discussed in the following.

Petersen et al. (2005) mention that there is a “golden” zone for shelf heights (between hip and shoulder height), where picking items is less exhausting for workers. The authors also state that this aspect has not yet been accounted for in stowage location planning models. Only recently, ergonomic considerations have been integrated into mathematical optimization and decision support models.

Battini et al. (2016b) investigate the optimal storage location for items in a single aisle consisting of a single (long) shelf. The authors consider a bi-criterial objective function, which minimizes total picking time as well as total ergonomic strain, depending on the vertical as well as horizontal placement of items. Ergonomic strain is quantified by calculating energy expenditure rates based on the concept developed by Garg et al. (1978). Another recent example of an application of the method by Garg et al. (1978) to quantify the ergonomic strain of picking items from different shelf configurations is the paper of Calzavara et al. (2017).

Larco et al. (2017) consider the problem of optimally stowing items in a warehouse with the objectives of minimizing travel time and ergonomic strain. They formulate this problem as an assignment problem, where every assignment of an item to a stowage location leads to a specific travel time and ergonomic strain. Besides the stowage location in the planar dimension, the authors also take the location in the vertical dimension (i.e., shelf heights) into account. Both travel times and ergonomic strains are determined in empirical experiments.

Otto et al. (2017) consider an item-to-storage assignment problem in a fast pick area using gravity flow racks.
The authors develop a tabu search heuristic in order to minimizing the pickers’ ergonomic strains, which they quantify using two different approaches; the NIOSH lifting equation (Waters et al., 1993) and a predetermined motion energy system (cf. Battini et al., 2016a) based on the model by Garg et al. (1978).

Some researchers have recently started to investigate ergonomics in line-side operations in an in-house logistics and production context. Neumann and Medbo (2010), for example, compare the use of EURO pallets to small containers in the Swedish automotive industry. The authors find that using narrow containers for line-side operations offers economic advantages due to lower item access times, and that this concept also substantially lowers ergonomic strain on workers handling the materials. Ergonomic strains are evaluated with the help of a biomechanical model that measures the load on the lumbar spine, shoulders and hands of the worker, implemented in the software 4D WATBAK (Neumann et al., 1999).

Palmerud et al. (2012) conduct a case study at a Swedish car manufacturer, where the authors compare the ergonomic strains of two alternative production strategies, namely long-cycle parallelised flow assembly and serial flow assembly. The second strategy is shown to lead to lower MMH stress. To assess ergonomic strains, the authors measure relevant values, such as step frequency, cardiovascular load and body posture, by means of video recordings and direct technical measurements on the workers. The measurements are then statistically refined and directly compared to assess differences in ergonomic strains between both production strategies.

Otto and Scholl (2011) integrate an ergonomic risk factor into an optimization model for assembly line balancing. They show that their model is suited for various different ergonomic risk evaluation approaches, namely the revised NIOSH equation (Waters et al., 1993), OCRA (Occhipinti, 1998) and EAWS (Schaub et al., 2013), but settle for OCRA in their final computational study.

To the best of our knowledge, such techniques have never been applied to stowage planning for tow train operations.

3. Problem description

Regarding the planning hierarchy, we assume the problem of optimizing the bin stowage of a tow train with regard to ergonomic aspects follows last, after tours, schedules and loads have been set. This is due the observations we made in practice and those reported in the literature, where operating the tow train economically is the primary goal. Therefore, optimizing tow train operations from an ergonomics point of view may most likely only be approved withing those boundaries set by economically optimal plans and schedules.

The ergonomic tow train loading problem (ETTLP) consists of assigning a given set of bins to storage slots on the tow train. Let $B = \{1, \ldots, n\}$ be the set of bins to be stowed on the tow train. Each bin $j \in B$ is assigned to a specific workstation $s(j) \in \mathbb{N}^{\neq 0}$ on the shopfloor. Note that one station may of course receive multiple bins, i.e., $s(j)$ may be identical for multiple $j$. If multiple bins are destined for the same station, they must not be divided among multiple wagons because this causes confusion and additional walking effort during unloading. Let $W = \{1, \ldots, w\}$ be the set of wagons to be loaded. Each wagon $w \in W$ has $m_w$ slots for bins in total, each $\mu$ bins deep, meaning that the total capacity of the tow train is $\sum_{w \in W} m_w \cdot \mu$ bins. Note that in many practical applications, we can assume $m_w = m_{w'}, \forall w, w' \in W$, i.e., all wagons are identical. Without loss of generality, we assume that $n = \sum_{w \in W} m_w \cdot \mu$, i.e., there are exactly as many bins as there is space. Note that this can always be imposed by adding “ghost” bins that do not contribute to the objective and have to be delivered each to a different “ghost” station. Also note that we assume that the total number of slots $\sum_{w \in W} m_w \cdot \mu$ is polynomially bounded by the number $n$ of (non-ghost) bins. We denote the set of slots as $P = \{1, \ldots, m\}$, where $m = \sum_{w \in W} m_w$. Each slot $p \in P$ is located on one wagon $w(p) \in W$. Placing a bin $j \in B$ in a slot $p \in P$ causes ergonomic strain on the logistics worker, denoted as $e(j, p)$. We explain in more
detail in Section 5.1.2 how \(e(j,p)\) can be calculated in practice.

A solution is defined as a mapping \(\rho : B \rightarrow P\) such that \(\rho(j) = p\) if bin \(j \in B\) is assigned to slot \(p \in P\). We call a solution feasible if and only if it satisfies the following conditions.

- No slot is loaded over capacity, i.e., since we use “ghost” bins to fill up empty spaces, for all \(p \in P\), it must hold that \(|\{j \in B \mid \rho(j) = p\}| = \mu\).
- Bins that are destined for the same station must be on the same wagon, i.e., for each pair of bins \(j, j' \in B\), it must hold that if \(s(j) = s(j')\), then \(w(\rho(j)) = w(\rho(j'))\).

The latter condition enables us to stop the tow train at each station such that the wagon that stores the bins destined for the respective station is located right in front of it. This implies that no workstation receives more bins than can be stowed on a single wagon. Enforcing this condition minimizes the walking distance of the worker unloading the tow train, which, firstly, minimizes the ergonomic strain that results from carrying loads, and, secondly, minimizes unloading times. Hence, we only consider stowage plans that do not worsen the tow train’s economic performance (i.e., unloading time), so that they are likely to be accepted in practice.

We further assume that slots are operated on a first-in-first-out principle, meaning that the bin that is put on a slot first is also the first one to be removed from it. This is the case, e.g., for gravity flow racks as described in Section 1. At each station, bins destined for this station should be directly available, without the need for reshuffling bins at any given slot. Provided that all bins are available at the beginning of the planning horizon, for any feasible solution of ETTLP, we assume that the tow train is loaded in such a way that reshuffles are avoided. Any feasible solution for ETTLP can be converted to a solution obeying the no-reshuffle condition via a sorting algorithm (sorting the bins in each slot according to their destined stations) in polynomial time (e.g., \(O(m \cdot \mu \cdot \log(\mu))\) using a comparison-based sorting algorithm). Therefore, we need not explicitly enforce this condition in our model.

A feasible solution already ensures that bins are stacked such that they can be accessed quickly. However, a feasible stowage plan does not guarantee that logistics workers can access bins in an ergonomic manner. To account for this, we seek among all feasible solutions one which minimizes

\[
\sum_{j \in B} e(j, \rho(j)).
\]

Note that, to formulate ETTLP concisely, we make the assumption that the capacity of the tow train is only limited by the number of bins it can carry, not by weight etc. This is usually a realistic assumption because tow trains are typically not used to carry bulky, heavy parts (Medbo, 2003). Moreover, we assume that the exact number of bins and their destinations on the shopfloor are known with certainty. This can be assumed to be a given in many just-in-time assembly systems (e.g., Emde and Gendreau, 2017, Emde, 2017) and is a requirement of the IT control system at our industry partner.

### 3.1. Example of an ETTLP solution

Consider an example with \(n = 8\) bins, which have to be loaded onto two wagons, each with \(m_1 = m_2 = 2\) slots, \(\mu = 2\) deep. Slots one and two are on wagon 1 (i.e., \(w(1) = w(2) = 1\)), and slots three and four are on wagon 2 (i.e., \(w(3) = w(4) = 2\)). The remaining parameters are given in Table 2a. A feasible and optimal solution is depicted in Figure 2b, corresponding to \(\rho(1) = \rho(2) = 1, \rho(3) = \rho(5) = 2, \rho(4) = \rho(8) = 3, \rho(6) = \rho(7) = 4\). This leads to a total objective value of \(1 + 2 + 2 + 3 + 7 + 2 + 9 + 11 = 37\).
3.2. MIP model for ETTLP

With the notation summarized in Table 1, we formalize ETTLP as a MIP model as follows.

\[
[\text{ETTLP}] \text{Minimize } f(x) = \sum_{p \in P} \sum_{j \in B} e(j, p) \cdot x_{p,j} \tag{2}
\]

subject to

- \(\sum_{p \in P} x_{p,j} = 1\) \quad \forall j \in B \tag{3}
- \(\sum_{j \in B} x_{p,j} = \mu\) \quad \forall p \in P \tag{4}
- \(\sum_{p \in P} w(p) \cdot x_{p,j} = \sum_{p \in P} w(p) \cdot x_{p,j'}\) \quad \forall j, j' \in B; j < j' \land s(j) = s(j') \tag{5}
- \(x_{p,j} \in \{0, 1\}\) \quad \forall p \in P; j \in B \tag{6}

Objective function (2) minimizes the total ergonomic strain of the stowage plan. Constraints (3) enforce that each bin is assigned to exactly one slot. Similarly, Constraints (4) ensure that exactly \(\mu\) bins (which can include “dummy” bins) are assigned to each slot, respectively. Equation (5) make it impossible for two bins destined for the same station to be on different wagons. Finally, (6) define the domain of the binary variables.
3.3. Time complexity

ETTLP is structurally similar to the generalized assignment problem (GAP, surveyed by Cattrysse and Van Wassenhove, 1992, Pentico, 2007, Burkard et al., 2012), which is well-known to be NP-hard. GAP is defined by a set of jobs and a set of agents, where agents have a limited capacity and assigning a job to an agent takes up capacity and incurs a certain cost. The goal is to assign each job to exactly one agent such that no agent’s capacity is exceeded and the total cost is minimal.

If we interpret slots as agents, bins as jobs, and ergonomic strain as cost, ETTLP comes fairly close to this definition. However, there is a number of differences, which obfuscate the complexity status of ETTLP. On the one hand, ETTLP is a special case in that all slots / agents have the same capacity $\mu$ and every bin / job takes up the same space (1 unit). On the other hand, ETTLP is a generalization of GAP, because the slots are not independent of each other: if a bin bound for a specific station is assigned to a slot, then all other bins bound for the same station must be assigned to slots on the same wagon. Two papers we are aware of that study somewhat related constraints are those of Roy and Słowiński (2006) and Caramia and Guerriero (2010), who propose a GAP model where there are mutually exclusive jobs that must not be assigned to the same agent.

Constraints for the linear assignment problem that force disjoint pairs of assignment variables to take the same value are considered by Aboudi and Nemhauser (1991) and Aboudi et al. (1991), called the couple constrained assignment problem. This type of constraint is different from ETTLP, however, because we do not care about specific pairs of assignments, only that slots be on the same wagon. Felici and Mecoli (2007) consider the assignment problem with preference conditions, which is similar to the couple constrained assignment problem, except that setting pairs of assignment variables to different values does not make the solution infeasible but affects the objective value. The constraints of ETTLP have, to the best of our knowledge, not yet been considered.

Note that GAP is not NP-hard if the capacity of each agent is 1 and each job takes unit capacity; in this case GAP is equivalent to the classic linear assignment problem, which is solvable in polynomial time (Burkard et al., 2012). However, this is not true for ETTLP, as we show in the following.

**Theorem 3.1.** Finding a feasible solution to ETTLP is NP-complete in the strong sense, even if the slot capacity is restricted to $\mu = 1$.

**Proof.** First, membership in NP is easy to see: an assignment of bins to slots constitutes a certificate. Under the assumption that the number of slots is polynomially bounded by the number of bins, such a certificate can obviously be verified in polynomial time.

We prove NP-hardness by pseudopolynomial reduction from 3-PARTITION, which is well known to be NP-hard in the strong sense (Garey and Johnson, 1979).

**3-PARTITION** is defined as follows: Given 3q positive integers $a_i$, $i = 1, \ldots, 3q$, and a positive integer $Q$ with $Q/4 < a_i < Q/2$ and $\sum_{i=1}^{3q} a_i = qQ$, does there exist a partition of the set $\{1, \ldots, 3q\}$ into $q$ sets $\{A_1, \ldots, A_q\}$, each having exactly three elements, such that $\sum_{i \in A_l} a_i = Q$ for each $l = 1, \ldots, q$?

We transform an instance $I$ of 3-PARTITION to an instance $I'$ of ETTLP in pseudopolynomial time as follows. We introduce a total of $qQ$ bins, i.e., $B = \{1, \ldots, qQ\}$, and $q$ wagons, each with $Q$ slots, i.e., $P = \{1, \ldots, qQ\}$ and $w(p) = l$, $\forall l = 1, \ldots, q$, $p = (l - 1) \cdot Q + 1, \ldots, l \cdot Q$. Each slot has a capacity of $\mu = 1$. The tow train supplies $3q$ stations, and each station’s demand corresponds to one integer from the 3-PARTITION instance, i.e., $s(j) = i$, $\forall i = 1, \ldots, 3q$, $j = \sum_{i=1}^{l-1} a_{i'} + 1, \ldots, \sum_{i'=1}^{l} a_{i'}$. We say that the bins $j \in B$ destined for station $i$ (i.e., where $s(j) = i$) correspond with integer $a_i$ from the 3-PARTITION instance.

A solution to 3-PARTITION instance $I$ can be transformed to an ETTLP solution by assigning the bins...
corresponding to the integers in each set $A_l$, $l = 1, \ldots, q$, to one wagon each. The sum of integers in set $A_l$ equals $Q$, which is also the number of slots on each wagon. Since the bins corresponding to the same integer are destined for the same station, the solution is feasible.

Conversely, a solution to ETTLLP instance $I'$ can also be converted to a solution for $I$. Each wagon holds exactly $Q$ bins. Bins bound for the same station must not be split onto different wagons. The total capacity of all wagons is $qQ$, which is also the total number of bins. Therefore, the only feasible way of stowing the bins is to put exactly $Q$ bins bound for exactly 3 destinations on each wagon. The correspondence with 3-PARTITION is hence apparent. An example is depicted in Figure 3.

![Figure 3: Example ETTLLP solution for a 3-PARTITION instance with $q = 3$, $Q = 20$ and integers $6, 6, 6, 6, 7, 7, 8, 8$; bins of the same shade are destined for the same station.](image)

### 4. Algorithms for ETTLLP

Given Theorem 3.1, even finding a feasible solution is bound to be computationally challenging for instances of realistic size. Nevertheless, we propose an exact solution procedure based on the observation that if an assignment of bins to wagons is given, the remaining subproblem of placing the bins in individual slots can be modeled as a linear assignment problem. We explain the decomposition in Section 4.1 and propose an exact solution procedure based on dynamic programming in Section 4.2.

Even though our computational experiments (Section 5) bear out that our exact solution procedure is faster than a default solver (CPLEX) and is able to solve many large instances of realistic size in acceptable time, its runtime still grows exponentially. We therefore also propose a heuristic procedure in Section 4.3, exploiting the decomposability of ETTLLP, to still be able to find solutions even for very large problem sizes.

#### 4.1. Decomposition of ETTLLP

To solve ETTLP, we decompose the problem into two stages: first, assigning bins to wagons and, second, assigning bins to slots. In the following sections we look at each decision individually, starting with the second problem.

##### 4.1.1. Assigning a given set of bins to slots of a given wagon

For this subproblem, we assume that we are given a set $B_{w'} \subseteq B$ of bins to be put on some wagon $w'$. To ease notation, let $S = \{s(j) \mid j \in B\}$ be the set of all stations. Furthermore, let $P_{w'} = \{p \in P \mid w(p) = w'\}$ be the set of slots located on wagon $w'$. We assume that no more bins are assigned to wagon $w'$ than it has space available, i.e., $|B_{w'}| \leq m_{w'} \cdot \mu$; otherwise, there is obviously no feasible assignment. If $|B_{w'}| < m_{w'} \cdot \mu$, we add “ghost” bins (with an ergonomic strain of zero) to $B_{w'}$ such that $|B_{w'}| = m_{w'} \cdot \mu$ becomes true. Finally,
we define $\tilde{P}_{w'} = P_{w'} \times \{1, \ldots, \mu\}$ as the set of tuples $t = (p, k)$ of slots of set $P_{w'}$ and individual positions in those slots, respectively. We can then formulate the following integer program using the additional notation in Table 2. We refer to this problem as the bin to position assignment problem (BTPAP).

<table>
<thead>
<tr>
<th>$B_{w'}$</th>
<th>set of bins assigned to wagon $w'$ (index $j$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{P}_{w'}$</td>
<td>set of positions on wagon $w'$ (index $t$)</td>
</tr>
<tr>
<td>$y_{t,j}$</td>
<td>binary variable: 1, if bin $j$ is assigned to slot-position $t$; 0, otherwise</td>
</tr>
</tbody>
</table>

Table 2: Additional notation.

\[
[BTPAP] \text{Minimize } g(y) = \sum_{t=(p,k) \in \tilde{P}_{w'}} \sum_{j \in B_{w'}} e(j,p) \cdot y_{t,j} \tag{7}
\]

subject to
\[
\sum_{t \in \tilde{P}_{w'}} y_{t,j} = 1 \quad \forall j \in B_{w'} \tag{8}
\]
\[
\sum_{j \in B_{w'}} y_{t,j} = 1 \quad \forall t \in \tilde{P}_{w'} \tag{9}
\]
\[
y_{t,j} \in \{0, 1\} \quad \forall t \in \tilde{P}_{w'}; j \in B_{w'} \tag{10}
\]

Objective function (7) minimizes the total ergonomic strain of the assignment. Constraints (8) and (9) ensure that each bin is assigned to exactly one position and vice versa. Finally, Constraints (10) restrict the domain of the variables to $\{0, 1\}$.

This problem is equivalent to the linear assignment problem. It can be solved in a polynomial runtime of $O((m_{w'} \cdot \mu)^3)$ using the formulation of Munkres (1957) of the Hungarian algorithm.

### 4.1.2. Assigning bins to wagons

The superordinate problem consists of assigning all bins to the tow train’s wagons (but not to individual slots). A partition of bins among wagons is feasible if no two bins destined for the same station are in different sets, i.e., placed on different wagons, and no set contains more bins than a wagon has slots, i.e., no wagon is overloaded.

Seeing that bins destined for the same station cannot be split up anyway, instead of considering each bin individually, we can pool the bins according to their destined station. We define the set of bins destined for station $s'$ as $J_{s'} = \{ j \in B \mid s(j) = s' \} \forall s' \in S$. We further define $\Lambda = \{ \lambda_1, \ldots, \lambda_{|W|} \}$ as a $|W|$-partition of the set of stations $S$, with each $\lambda_l$, $l \in \{1, \ldots, |W|\}$, being a disjunct subset of $S$ and $\bigcup_{l \in \{1, \ldots, |W|\}} \lambda_l = S$. The problem then becomes to find a $|W|$-partition $\Lambda$ of the set of stations $S$, such that $\sum_{s \in \lambda_l} |J_s| \leq m_l \cdot \mu$, $\forall \lambda \in \{1, \ldots, |W|\}$.

Note that to evaluate a given partition $\Lambda$, we need to solve the subordinate linear assignment problem from Section 4.1.1 for each of the wagonloads $\lambda_l$, $\forall l \in \{1, \ldots, |W|\}$. However, finding one feasible partition is adequate to obtain one feasible solution to the ETTLP, a fact which we will later use in our heuristic procedure.

Note that this subproblem is similar to the multi-way number partitioning problem, which consists of finding a $|W|$-partition of a set containing $|S|$ integer elements, such that the difference between the sums of the integers of each of the partition’s subsets is minimal. This problem is known to be NP-hard (Korf, 2009). The partitioning problem is also similar to variable-sized bin packing (Friesen and Langston, 1986), which is a
generalization of bin packing where bins may have different capacities. Unlike bin packing, however, the exact number and capacity of bins (wagons) is given and not a variable.

4.2. An exact algorithm based on dynamic programming

To solve ETTLP exactly, we propose the following procedure. We use a dynamic programming scheme, based on the general idea formulated by Bellman (1954), to find the optimal partition of bins to wagons and assignment of bins to slots.

The dynamic program (DP) consists of $|W| + 1$ stages (with index $r = 0, \ldots, |W|$), each stage containing states $(\Gamma)$, where $\Gamma \subseteq S$ denotes the set of stations whose bins have already been assigned to wagons. Starting from the initial stage $r = 0$ with state $\Gamma = \emptyset$, each successor in stage $r+1$ is reached by adding a subset $\lambda \subseteq S \setminus \Gamma$ to $\Gamma$, i.e., the bins destined for the stations in set $\lambda$ are assigned to wagon $r$. We only consider successors that still can lead to feasible assignments, and, thus, do not violate the following two criteria.

1. The number of bins destined for the stations contained in $\lambda$ must not be greater than the wagon’s capacity, i.e., $\sum_{s \in \lambda} |J_s| \leq m_r \cdot \mu$ must hold.

2. For the bins destined for the stations that are not yet assigned, there must still be enough space left on the remaining wagons, i.e., $\sum_{s \in S \setminus (\lambda \cup \Gamma)} |J_s| \leq \sum_{r' = r+1}^{r' = |W|} m_{r'} \cdot \mu$ must hold.

Furthermore, we can accelerate our DP by breaking symmetries that may occur in most real-world instances. In many realistic cases, all wagons of the tow train are identical. This implies that, first, every wagon has the same capacity, and second, each wagon holds ergonomically identical sets of slots, because the latter mostly depends on the vertical height of the respective slot; e.g., all slots on the middle shelf of each wagon may be equally accessible. In such cases, we do not care which of the identical wagons a given partition $\lambda$ is assigned to. Therefore, if all wagons are equal, we break symmetries by only considering successors according to the following rule.

3. We only add $\lambda$ to $\Gamma$ if $\min \{ s \in \lambda \} < \min \{ s \in S \setminus (\Gamma \cup \lambda) \}$ holds true.

Using this rule, we enforce that the subsets in each generated partition are in a particular order. To be specific, $\lambda$ has to contain a station with a smaller index than the smallest one of any $\lambda'$ added at a later stage. By doing so, we avoid the need to evaluate every permutation of a given partition, which (in the symmetric case) all yield the same objective value. Instead we only evaluate one permutation; the one, whose subsets are ordered in the way we demand.

Let $V(\Gamma)$ be the set of states from which a transition to state $\Gamma$ exists. The optimal objective value $h(\Gamma, r)$ can then be calculated recursively as

$$h(\Gamma, r) = \min_{\Gamma' \in V(\Gamma)} \left\{ h(\Gamma', r - 1) + g^* \left( \bigcup_{s \in \Gamma \setminus \Gamma'} J_s, r \right) \right\},$$

with $h(\emptyset, 0) = 0$ for the initial state and $g^*$ being the optimal objective value of the BTPAP from Section 4.1.1 for the given set of bins $\bigcup_{s \in \Gamma \setminus \Gamma'} J_s$ and the given wagon $r$. The objective value of a complete solution in final state $\Gamma = S$ equals $h(S, |W|)$, which is also the optimal objective value for ETTLP. We can obtain the corresponding optimal assignment by backward recovery along the optimal path.

Concerning the time complexity, note that the total number of different possible partitions is in $O\left(\binom{|S|}{|W|}\right)$, where $\binom{|S|}{|W|}$ denotes the Stirling number of the second kind. The number of nodes in the DP graph is bounded
by $O(|W| \cdot 2^{|S|})$, while the number of transitions cannot be greater than $O(|W| \cdot 2^{|S|})$. For each transition, to calculate the contribution to the objective value, a linear assignment problem must be solved, which can be done in $O(n^3)$ time using, e.g., the improved Hungarian method. Hence, the worst-case total number of steps required for DP is bounded by $O(n^3 \cdot |W| \cdot 2^n)$. Note, however, that due to the exclusion rules laid out above, the actual number of steps is usually much lower.

**Example (cont.):** The dynamic programming graph for the problem given in Section 3.1 is depicted below. One optimal solution (all three possible solutions are optimal in this example) is bold, corresponding to the first wagon receiving the bins bound for stations 1 and 3, and the second wagon receiving the bins bound for the remaining stations 2, 4, and 5. This corresponds to the solution depicted in Figure 2b.

![Dynamic programming graph](image_url)

**Figure 4:** Dynamic programming graph for the example given in Section 3.1.

4.3. A GRASP metaheuristic

Seeing that the asymptotic runtime of our DP scheme is exponential, we propose a heuristic algorithm based on greedy randomized adaptive search (GRASP) to obtain good solutions for large instances in acceptable time. GRASP, as originally proposed by Feo and Resende (1995), consists of the following steps: first, an initial solution is obtained using a randomized constructive heuristic. Second, this solution is improved by performing a local search on it. Steps one and two are repeated several times until the stopping criterion is satisfied. Finally the best found solution is returned.

Adapting this scheme to ETTLP is not entirely straightforward because, by Theorem 3.1, even finding a feasible solution is already NP-hard. In Section 4.3.1, we describe how we generate initial solutions that are at least close to feasible. We repair and improve these solutions via a matheuristic local search approach in Section 4.3.2, and put both components together in a GRASP framework in Section 4.3.3.

4.3.1. Randomized constructive heuristic

What makes ETTLP difficult is finding the best $|W|$-partition of $S$. By Theorem 3.1, even finding a single feasible partition is NP-hard. Therefore, we use the GRASP framework to obtain feasible partitions, for which we then find the optimal assignment in a successive step. To do this, we formulate a relaxed version of the partitioning problem from Section 4.1.2 by allowing the number of bins assigned to the wagons to be greater than their capacity, i.e., we accept partitions $\Lambda$ for which the condition $\sum_{s \in \lambda_i} |J_s| \leq m_l \cdot \mu, \forall l \in \{1, \ldots, |W|\}$, does not hold.
To attain initial solutions that are at least close to feasible partitions for ETTLP, we propose the constructive heuristic outlined in Algorithm 1. This procedure is similar to the greedy heuristic classically used in multi-way number partitioning. The greedy multi-way number partitioning heuristic first orders all integers according to non-increasing values. It then assigns them one by one to the subset with the currently smallest sum of integers until all integers are partitioned (Korf, 2009). However, this procedure does not contain any randomization, which is needed for GRASP in order to obtain different initial solutions. We therefore alter the procedure as follows.

First, we order all stations randomly, and thereby add the required randomness to the procedure. We go through the stations one-by-one to assign the bins destined for it to a wagon. Let \( S_w \subseteq S \) be the set of stations whose bins have already been assigned to wagon \( w \) (initially, \( S_w = \emptyset \)). Furthermore, let \( s' \) be the station we are currently looking at. We use the following decision criteria to choose a wagon to assign station \( s' \) to. If there is a wagon \( w' \) that is filled exactly to capacity if all bins bound for station \( s' \) are added to the bins already assigned to that wagon, we choose \( w' \). I.e., if \( \sum_{s \in S_w \cup \{s'\}} |J_s| = m_{w'} \cdot \mu \), we choose \( w' \). If no such wagon exists, we choose the currently least filled one, i.e., we choose \( w' = \text{arg min}_{w \in W} \{ \sum_{s \in S_w} |J_s| \} \). Ties are broken randomly. These steps are repeated until all bins are assigned.

Algorithm 1: Randomized constructive heuristic for the relaxed version of ETTLP.

```
Input: instance of ETTLP
1 \( \zeta(s) := -1, \forall s \in S \); // wagon to which bins bound for station \( s \) are assigned
2 \( \eta(w) := 0, \forall w \in W \); // the number of bins currently assigned to wagon \( w \)
3 foreach \( s \in S \) in random order do
   4 \( \Omega := \emptyset \); // set of wagons for selection
   5 for \( w = 1 \) to \( |W| \) do
      6 if \( \eta(w) + |J_s| = m_{w'} \cdot \mu \) then
         7 \( \Omega := \Omega \cup \{w\} \);
   8 if \( \Omega = \emptyset \) then
      9 \( \eta_{\text{min}} := \min_{w \in \Omega} \{\eta(w)\} \);
     10 \( \Omega := \{w \in W | \eta(w) = \eta_{\text{min}}\} \);
     11 \( \zeta(s) := \text{rand}(w \in \Omega) \); // random tie break
     12 \( \eta(\zeta(s)) := \eta(\zeta(s)) + |J_s| \);
Output: Assignment of stations to wagons \( \zeta \)
```

4.3.2. Local search via mixed-integer programming

The solution constructed by Algorithm 1 may not be a feasible partition for ETTLP because individual wagons may be loaded over capacity. Thus, we present a local search algorithm to improve upon the initial solution and, thereby, hopefully make it a feasible partition for ETTLP.

We propose an IP-based heuristic improvement method, related to the idea of the local branching scheme originally introduced by Fischetti and Lodi (2003). The idea of local branching is to divide the feasible region of a problem into multiple smaller regions by adding invalid cuts to the MIP model in each branch of the branching tree. Each of these MIP models are then solved by a black box default solver. This allows taking advantage of the sophistication of modern off-the-shelf solvers, which are generally good at solving small integer programs. Roughly summarized, local branching consists of the following steps. Starting from an initial integer solution \( \bar{\zeta} \), an invalid cut is added to the MIP reducing the solution space to a region in proximity to \( \bar{\zeta} \). Within this region the best solution is obtained using a default solver. If the objective value is improved, \( \bar{\zeta} \) is set to the new found solution and the procedure is repeated, while the solution space that has already been evaluated is excluded. When using local branching heuristically as a local search procedure, one does not care for the entire
solution space, but only the local surroundings of a given solution $\zeta$. The procedure can thus be aborted as soon as no improving solutions in the immediate neighborhood of $\zeta$ can be found. Local branching strategies have previously been successfully employed in heuristics for, e.g., the open pit mine production scheduling problem (Samavati et al., 2017), the capacitated fixed-charge network design problem (Rodríguez-Martín and Salazar-González, 2010), and the railway rescheduling problem (Acuna-Agost et al., 2011).

| $\delta_w$ | binary variable: 1, if the amount of bins assigned to wagon $w$ exceeds its capacity; 0, otherwise |
| $z_{w,s}$ | binary variable: 1, if the set of bins destined for station $s$ is assigned to wagon $w$; 0, otherwise |

Table 3: Additional notation for RBTWP.

Let $\zeta$ be a solution obtained from Algorithm 1, and let $S_w$ be the corresponding set of stations whose bins are assigned to wagon $w$, $\forall w \in W$. Assume that this solution is infeasible with regard to the non-relaxed problem, where the capacity of the wagons is limited. Let $\overline{W} = \{ w \in W \mid \sum_{s \in S_w} |J_s| > m_w \cdot \mu \}$ be the set of wagons whose capacity is exceeded. Using the notation in Table 3, we formulate the IP given below, similar to the scheme proposed by Fischetti and Lodi (2008). We refer to this subproblem as the relaxed bin to wagon problem (RBTWP).

\[
\text{[RBTWP]} \quad \text{Minimize } h(z, \delta) = \sum_{w \in \overline{W}} \delta_w
\]

subject to

\[
\sum_{w \in W} z_{w,s} = 1 \quad \forall s \in S
\]

\[
\sum_{s \in S} |J_s| \cdot z_{w,s} - n \cdot \delta_w \leq m_w \cdot \mu \quad \forall w \in \overline{W}
\]

\[
\sum_{s \in S} |J_s| \cdot z_{w,s} \leq m_w \cdot \mu \quad \forall w \in W \setminus \overline{W}
\]

\[
z_{w,s} \in \{0, 1\} \quad \forall w \in W; s \in S
\]

\[
\delta_w \in \{0, 1\} \quad \forall w \in \overline{W}
\]

The objective (11) is to minimize the number of wagons whose capacity is exceeded. Constraints (12) ensure that every set of bins destined for the same station is assigned to exactly one wagon. Constraints (13) force $\delta_w$ to assume value 1 if the capacity is exceeded at wagon $w$, whereas Inequalities (14) enforce the capacity constraint for the non-critical stations. Finally, (15) and (16) define the domain of the decision variables.

In a classic local branching approach, we would now add an invalid cut to define the region of proximity to $\zeta$, before solving it with a default solver. However, our problem has special properties which lead us to take a different approach. Note that we only care about RBTWP solutions that yield an objective value of zero, since only these are feasible partitions for ETTLP. More often than not, solutions with low (but greater than zero) objective value are nowhere near solutions with an objective value of zero. For an extreme example, consider a solution where we assign every bin to a single wagon. This solution yields an objective value of one, since only one wagon’s capacity is violated. However, the solution is as far from an optimal solution (with an objective value of zero) as it can be.
Consequently, we alter the definition of locality. Classic local branching cuts have the disadvantage that the cuts define strict borders. If an optimal solution lies just marginally outside of these borders (i.e., is just a little too different from the current incumbent solution \( \overline{z} \)), it cannot be reached. In the original local branching procedure, this is mitigated by the branching process, which shifts the region of locality at every branch. However, since we evaluate only one branch, this is not the case for our approach. We therefore define locality differently, via runtime.

Our idea is to not apply any cuts to RBTWP at all, but to solve the whole problem at once, using a default solver. To ensure short computation times, we set a narrow time limit for the solver, which restricts it to only evaluate a few solutions. This allows us to use the full advantage of modern default solvers, which generally perform well at finding good (or even optimal) solutions quickly and take most of their time to prove optimality. Hence, we define those solutions to be in the locality of a given solution \( \overline{z} \) that are found within a maximum time \( T \) by a black box default solver, which is warm started from solution \( \overline{z} \).

Note that our computational test shows this approach to work very well on instances of realistic size (see Section 5). However, if the problem size gets too large, additionally adding invalid cuts in the classic way might be reasonable. This turns out to not be necessary for even the largest instances we tested, however.

### 4.3.3. GRASP framework

We can now perform a classic GRASP to find solutions for RBTWP, such that each obtained solution that yields an objective value of zero is a feasible partition for ETTLP. Therefore, each time we find such a solution, we solve the emerging BTPAP linear assignment problem for each wagon (see Section 4.1.1) to get a viable solution for ETTLP. Else, if no feasible partition can be found within the time limit of \( T \), we scrap the current solution and perform the next iteration of our GRASP. The framework of this heuristic is outlined in Algorithm 2.

**Algorithm 2: GRASP heuristic for ETTLP.**

**Input:** instance of ETTLP

1. \( f^* := \infty \); // best found objective value for ETTLP
2. instance of RBTWP := create instance of RBTWP( instance of ETTLP );
3. while stopping criterion not satisfied do
4.     \( z := \) randomized constructive heuristic( instance of RBTWP );
5.     \( z := \) local search(\( z \));
6.     if \( h(z) = 0 \) then // solution is feasible
7.         \( f := 0 \);
8.         for \( w \in W \) do
9.             \( y := \) solve BTPAP for given partition \( z \) and wagon \( w \);
10.            \( f := f + g(y) \);
11.            if \( f < f^* \) then
12.                store new best solution;
13.                \( f^* := f \);
6.     \( f := f + g(y) \);
7.     if \( f < f^* \) then
8.         store new best solution;
9.     \( f^* := f \);
10. \)

**Output:** ETTLP solution

### 5. Computational study

In this section, we test the computational performance of our exact and heuristic solution procedures. We compare both procedures to each other as well as to a default solver (CPLEX). To do so, we randomly generate realistic test instances of various sizes, which we describe in detail in the following subsection. We also derive
some managerial insights, namely to what extent pursuing ergonomic objectives can actually relieve the strain on the workforce compared to classic purely economic objectives, and how the layout and the filling of the tow train affects its ergonomic performance.

5.1. Benchmark instances and ergonomic assessment

Since, to the best of our knowledge, there has not yet been any research into stowing bins ergonomically on tow trains, there are no benchmark instances available to test our proposed procedures. Therefore, we create new ones. In the following, we first explain the general procedure of generating our instances. Afterwards, we explain how we obtained realistic ergonomic values.

5.1.1. Generating instances

ETTLP is the last of a sequence of optimization problems concerning tow trains. At first, routing, scheduling, and loading problems have to be solved (see Section 2). The results of those problems then define the input for ETTLP. In practice, tow train routing, scheduling and loading are solved in a way that leaves enough flexibility to properly stow the bins on the tow train. We therefore create our instances by first randomly generating a tow train stowage plan, imitating the way tow trains are typically loaded in practice, that is, without considering ergonomic stress. We call this the “default” or “status-quo” stowage plan.

The size of an instance is defined by parameters $n$, the number of bins, $m$, the number of slots, $\mu$, the capacity per slot, $|W|$, the number of wagons and $|S|$, the number of stations. Note, that $n \leq \mu \cdot m$ must hold, or else the tow train’s capacity is exceeded. Further, if $n = \mu \cdot m$, the tow train is filled completely. Else, if $n < \mu \cdot m$, the tow train is only partially filled. Beyond that, $\frac{m}{|W|}$ is the number of slots per wagon and must be commensurate with the wagons’ layout. For example, if each wagon has three different shelf heights, with each shelf holding three slots, giving a total of 9 slots per wagon, $\frac{m}{|W|} = 9$ must hold.

An instance is generated by assigning every bin $j = 1, \ldots, n$ to a random slot and a random position within this slot that has not yet been filled. We then assign every station $s = 1, \ldots, |S|$ randomly to a wagon, where we make sure that to every wagon at least one station is assigned. Stations are attached to bins by randomly choosing one of the stations assigned to the respective wagon, ensuring that every station is assigned to at least one bin, and every bin to exactly one station.

Finally, we need to tackle the ergonomic strain. Since the ergonomic strain caused by placing a certain bin in a certain slot is dependent on the weight of the bin and the vertical location of the slot, we need to assign weights to every bin and heights to every slot. For every bin we randomly draw a weight from a discrete set of weights $\Theta$. Vertical heights are assigned to slots according to the layout of the tow train’s wagons. In each wagon, the slot with the lowest index is located on the bottom shelf on the left. With increasing indices, the slots are first located further to the right until the shelf has no slots left. After that, slots are located on the next higher shelf until the slot with the highest index is located at the right end of the top shelf of each wagon, respectively. Note that bin weights and slot heights are only auxiliary parameters we use to calculate the ergonomic strains $e(j, p)$, $\forall j \in J; p \in P$. We calculate ergonomic strains for two representative workers, one male and one female. The subsequent Section 5.1.2 explains in more detail, how the ergonomic strains are derived.

In accordance with our observations in practice, we choose our default wagon to have three different shelf heights, 30 cm, 95 cm and 160 cm at the side from which the shelf is unloaded, with additional 15 cm of height at the opposite side since the shelf is constructed as a gravity flow rack. Each shelf holds three slots next to each other, and each slot has space for $\mu = 3$ bins, such that a wagon can hold $3 \cdot 3 \cdot 3 = 27$ bins in total. Bin weights are drawn from $\Theta = \{5, 10, 15, 20, 30\}$ kg, since those are quite representative weights in industrial
environments (e.g., Drury et al., 1982). Bin measurements are set to 30 cm in width, 40 cm in length and 21.3 cm height, which is in accordance with a standardized recommendation of the German automotive industry (VDA, 2018).

Once we are done with those assignments, we can derive all parameters needed for an instance of ETTLP, namely $B, P, \mu, s(j), \forall j \in J, w(p), \forall p \in P,$ and $e(j,p), \forall j \in J; p \in P$. To test the performance of our proposed solution procedures we generate and solve instances of various realistic sizes. According to Boysen et al. (2015), in practice, the number of wagons per tow train rarely exceeds more than a handful. During each milk-run, the tow train visits multiple stations, but the number of stations visited exceeds the number of wagons per tow train just by a few most of the time. Therefore, to represent different scenarios, we create instances of three different sizes, small, medium and large with $|W| = 2$ and $|S| = 3$, $|W| = 4$ and $|S| = 6$ as well as $|W| = 6$ and $|S| = 9$, respectively.

The number of slots per instance is derived by multiplying $|W|$ with a factor of 9, since this is the amount of slots our default tow train wagon holds. With each slot having a capacity of $\mu = 3$, the maximum number of bins the tow train can load amounts to $|W| \cdot 9 \cdot 3$. Since tow trains are commonly not loaded to their full capacity, for each instance size, we create two kinds of instances: one, where every single slot of the tow train is occupied by bins, and a more realistic one, where the tow train is loaded only to about 80% capacity. Note that instances of the latter kind do in fact contain the full number of bins, where we fill the remaining 20% with “ghost” bins, as described in Section 3. For each instance size and loading kind, we create ten random instances.

Each instance is named in the following way. From left to right, first, a letter characterizes the instance size, small (S), medium (M), or large (L). Then, another letter denotes if a representative male (m) or female (f) worker is used for determining ergonomic strains. Afterwards, a set of numbers characterizes the instance’s parameters in the following order: the number of bins $n$, followed by the number of non-“ghost” bins in brackets, the number of slots $m$, the slots capacity $\mu$, the number of wagons $|W|$ and finally the number of stations $|S|$. The two right-most digits are continuous counting numbers to identify each instance.

In total, we generate 260 instances, which are available from http://doi.org/10.5281/zenodo.2624216.

5.1.2. Measuring ergonomic strain

The manual unloading of racks – and, similarly, tow train wagons as in the case of this paper –, consists of three main activities that may expose the worker to a significant physical load: the pulling, lifting and lowering of objects. The manual handling of materials and its impact on the human body has traditionally been studied in the human factors engineering literature, cf., for example, the basic textbooks of Helander (2005) and Winter (2009). To assess MMH activities’ risks of increasing workers’ likelihood to develop MSD, the literature differentiates between four major approaches (Moore and Garg, 1995):

- the observation and subjective evaluation of MMH activities by highly qualified professionals,
- the examination of biomechanical, physiological and / or psychophysical critical threshold responses,
- the analysis of epidemiological data on the correlation of jobs, activities or other variables with increased risk of MSD,
- and combinations of the methods mentioned above.

Although professional judgment of MMH activities by specialists is a valuable method in practice, this approach, due to its subjectiveness, is less suitable to determine quantitative ergonomic strains (Moore and
Garg, 1995). The evaluation of epidemiological data, on the other hand, is a much more objective approach. However, epidemiological studies typically do not assess MMH via exact, quantitative values. Rather, they are designed to determine or verify the link between certain variables, activities or tasks to certain MSD (Dempsey, 1998). Therefore, and due to the fact, that epidemiological studies are very costly in terms of time, this approach is also less suited for our purposes.

The determination of different critical threshold responses is based on the observation that exceeding certain thresholds fosters the development of various MSD; the higher the limit is exceeded, the higher the likelihood of developing MSD. The emphasis of the biomechanical approach is the force or torque applied to certain joints or muscles during various MMH tasks, most commonly the lower back joints $L_4/L_5$ or $L_5/S_1$. The physiological approach focuses on a worker’s energy expenditure during a MMH task, i.e., the cardiovascular effort associated with performing the task. Lastly, psychophysical approaches considers a worker’s perceived strain for evaluating the task (Dempsey, 1998).

While it is possible to assess various threshold responses of workers performing MMH activities directly via measurements (e.g., via body-mounted sensors), this approach may interfere with and hence disturb the very activity it tries to evaluate. Therefore, to ease evaluation and to avoid intervening with task performance, models have been developed to calculate respective responses for a variety of MMH activities (Dempsey, 1998).

A physiological model that has enjoyed some popularity in the past both in research and in practice is the energy expenditure prediction model developed by Garg et al. (1978). It is based on the assumption that the energy expenditure rate of a composite task, such as (un-)loading a shelf, for example, can be calculated by summing up its comprising basic tasks’ energy expenditure rates. Energy expenditure rates of basic tasks depend on various task characteristics such as distances, heights, weights, forces and body positions, as well as anthropological characteristics of the person performing the task, like sex and body weight, and they can be calculated using equations that were derived by the authors via regression analyses of data obtained in laboratory experiments. The higher a composite task’s calculated energy expenditure rate, the greater its ergonomic strain. Prior research assumed that the maximum average energy expenditure rate an average person can tolerate over the course of an eight-hour workday is $5 \text{kcal/min}$, though this value is debated (Dempsey, 1998).

One of the advantages of the model of Garg et al. (1978) is its suitability for the evaluation of a multitude of MMH activities, making it very flexible in application (Dempsey, 1998). In addition, it is easier to handle than many biomechanical models. It offers the possibility to account for worker-individual data and has previously been used in various application areas (e.g., Garg et al., 1978, Waters et al., 1998, Glock et al., 2018) as well as in recent managerial approaches taking account of ergonomic aspects (cf. Section 2). Due to this flexibility and widespread use, we use the energy expenditure prediction model of Garg et al. (1978) to calculate the ergonomic strain for our instances.

The first step is to analyze the task of (un-)loading a tow train wagon, which in our case, is equipped with a gravity flow shelf, and to break this task down into basic tasks. To do this, we observed different workers (un-)loading shelves of different heights. We subdivided their movements into a set of basic tasks and derived the following generalized sequence for loading:

1. At the beginning of the loading process, the worker adopts an upright standing posture about 50 cm in front of the shelf, facing it. His legs are positioned slightly shifted. The worker grasps the bin with both hands at the centers of its sides, holding it at hip height, so that it is in contact with his hip and thighs.
2. The worker moves the bin right to the front of the shelf on which he wants to place it. This includes a movement of the hands, arms and shoulders in horizontal and in vertical direction. If the destined shelf is located below hip height, the worker has to squat in addition.

\(^2\)We use the male gender to refer to individuals of arbitrary gender.
3. The worker places the bin’s adverted bottom side on the rear edge of the shelf.
4. The worker moves his hands, one after the other, to the front of the bin to change grip.
5. The worker pushes the bin about halfway over the edge of the shelf.
6. The worker releases the bin, so that it is pulled onto the rack by gravity.
7. The worker returns to an upright standing posture, while aligning his hands, arms and shoulders with his torso, so that his hands come in contact with his outer thighs.
8. The loading movement ends.

For unloading, we observed the following sequence:

1. At the beginning of the unloading process, the worker adopts an upright standing posture about 50 cm in front of the shelf, facing it. His legs are positioned slightly shifted. The worker’s arms, hands and shoulders are hanging sideways, aligned with his torso. His hands are in contact with his outer thighs just below hip height.
2. The worker moves his hands to the front of the bin that he wants to unload. This includes a movement of the hands, arms and shoulders in horizontal and vertical direction. If the destined shelf is located below hip height, the worker has to squat in addition.
3. The worker lifts the bin’s front up slightly, so that its lower edge slips over the frontal edge of the shelf.
4. The worker pulls the bin about halfway over the edge of the shelf.
5. The worker moves his hands, one after the other, to the middle of the sides of the bin to change grip.
6. The worker pulls the bin off the shelf’s frontal edge to its full length.
7. The worker brings the bin vertically to hip height and horizontally to contact with his hip and thighs. Depending on the shelf height from which he gathered the bin, the vertical movement consists of lowering or lifting. If the bin was located below hip height, the latter also includes bringing the body to an upright posture again.
8. The unloading movement ends.

For additional clarification, both the loading and the unloading process are schematically depicted in Figures 6 and 7 in the appendix.

In addition to the basic tasks described above, the worker has to carry bins to the tow train during loading and carry bins to their destination during unloading. However, these activities are not part of the basic (un-)loading movement and cannot be influenced by optimizing the bins’ stowage on the tow train. Therefore, we do not include them in our ergonomic evaluation. Note that the general sequence of steps as listed above is independent of shelf height and bin weight. Only in some steps, it is necessary to differentiate between the precise movements (for example lifting versus lowering a bin in step 7 during unloading) that depend on the shelf height. Using the equations of Garg et al. (1978), this enables us to calculate the average ergonomic strain associated with loading and unloading an arbitrary weighted bin to / from an arbitrary shelf height. Hence, we calculate the ergonomic strain $e(j, p)$ arising from placing bin $j$ in slot $p$ as a function of the bin’s weight and the shelf’s height slot $p$ is located at.

For the sake of generality, in the proceedings of the computational study, we primarily use the anthropometric measurements of a representative worker, derived from the average worker’s anthropometrics we observed in practice. Our representative worker is male, weighs 75 kg and measures 178 cm in height, with a hip height
of 80 cm (cf., Glock et al., 2019). A similar approach of defining a representative worker is taken by Battini et al. (2016b) and Glock et al. (2019), for example. We acknowledge that individual workers (with different anthropometric measurements) can experience different ergonomic strains and may be able to tolerate varying thresholds without an increased risk of developing MSD. However, in the course of our computational study, we aim to provide a general estimate of the reduction in ergonomic strains that can be achieved by loading tow trains ergonomically. This reduction, expressed in relative terms, is approximately equal independent of the worker’s anthropometric measurements. We demonstrate the latter by additionally evaluating and optimizing the ergonomic strains for an average female worker weighting 61.9 kg and measuring 161.4 cm in height (cf., Tehard et al., 2002), which results in almost identical relative reductions (cf., Section 5.2). We further note that our model is not restricted to those anthropometric measurements; in practical applications different anthropometrics could be used.

Despite the mentioned advantages of the energy expenditure prediction model of Garg et al. (1978), this approach also has shortcomings. First of all, the assumption that a composite task’s energy expenditure rate is the sum of its basic tasks’ energy expenditure rates turned out to be questionable in various studies (Genaidy et al., 1985, Taboun and Dutta, 1989). This may lead to a systematic over-prediction of energy expenditure rates (Ayoub, 1992). However, since we compare very similar tasks to each other, i.e., (un-)loading from different rack heights, this systematic bias should be roughly the same for every task, so that comparisons of differences in the tasks’ energy expenditures should be still adequately accurate.

A second problem is that while we can compare the total energy expenditures resulting from different bin stowages on the tow train, this does not tell us exactly how the risk of developing MSD changes for the worker (un-)loading it (Ayoub, 1992, Dempsey, 1998). This is due to multiple reasons. First, an activity harmful for one worker may not negatively influence the health of another worker (Snook and Ciriello, 1991). Secondly, we do not know which activities the worker performs between loading and unloading the tow train. Reducing the ergonomic strain of (un-)loading tow trains is more beneficial, the higher the worker’s energy expenditure during further activities. Thirdly, even if we knew a worker’s exact energy expenditure rates over the course of his complete shift, there is a lack of statistics on how the risk of developing MSD is precisely linked to certain levers of energy expenditure rates (Ayoub, 1992, Dempsey, 1998).

The limitations mentioned above are not unique to the energy expenditure concept, but apply to ergonomic assessment methods in general (Ayoub, 1992, Dempsey, 1998); hence, selecting a different evaluation method would not solve this problem. We note, however, that we formulate the ETTLP in a way that ensures that improving the ergonomics assessment of the tow train does not worsen economic performance. The reduction in energy expenditure induced by our method improves the workplace quality for the tow train driver, even if we are unable to calculate an exact injury risk. Hence, the explanatory power of the energy expenditure concept is sufficient for the scope of this paper.

A last minor problem concerns the physical dimension of energy expenditure rates. Energy expenditure rates have the physical dimension of power (energy per unit of time). Summing up values in the dimension of power, as we do in our objective function, to find the optimal bin stowage results in an outcome value not representing any real-world physical property. However, we can calculate absolute energy expenditures for every task by multiplying its energy expenditure rate with the time it takes to perform the task. According to our observations in practice, every basic (un-)loading task, independent of shelf heights, takes about the same amount of time to be performed, which is roughly three seconds. Therefore, instead of using energy expenditure rates as a measurement of ergonomic strain, we use the absolute energy expenditure. Since we multiply every energy expenditure rate by the same time to obtain absolute energy expenditures, minimizing the sum of both objectives (i.e., energy expenditure rates or absolute energy expenditure) yields the same solution. In the later
case though, we can interpret the objective value as the total energy needed to (un-)load the tow train. Therefore, we use absolute energy expenditure values instead of rates.

5.2. Computational results

5.2.1. Computational performance

We solve each instance with our proposed DP and GRASP, and the MIP model with CPLEX (version 12.8), all implemented in C#. Computational testing was performed on an Intel Core i7-6700 CPU @ 3.40 GHz and with 8 GB of RAM. For all solution procedures, we set a maximum runtime of 3600 seconds (i.e. 1 hour). For GRASP, we set the number of iterations to 50 and the maximum runtime for the local search at each iteration to $T = 1$ second for all instances. Detailed reports of the results are available from http://doi.org/10.5281/zenodo.2624216. In the following, however, we mainly present the results of those instances that use the anthropometric measurements of a representative male worker for quantifying ergonomic strain. If not stated otherwise explicitly, we always refer to those instances. The main purpose of the instances, where the anthropometric measurements of an average female worker are used to quantify ergonomic strain, is to demonstrate, by comparison with the former instances, that the achievable relative reduction in ergonomic strains by (un-)loading a tow train ergonomically is virtually independent of the worker’s anthropometrics; hence that our evaluation is generalizable. The results for the instances that use the anthropometric measurements of the representative male worker are summarized in Table 4, 5 and 7. A comparison between the relative reduction in ergonomic strains for anthropometric measurements of either a representative male or female worker is given in Table 6.

Table 4 summarizes the results for instance, whose sizes are comparable to problem sizes in practical application. While CPLEX is able to prove optimality for all small and medium-sized instances within a runtime of 3600 seconds, it fails to do so for most of the large instances. DP, on the other hand, performs much faster. It can solve all realistic sized instances to proven optimality in not more than a tenth of a second, including large instances and, therefore, beats CPLEX runtime-wise on every single instance. GRASP performs well, too. For every realistic sized instance but four, GRASP finds the optimal solution. The single largest relative optimality gap is $3.50\%$ in instance L-m-162(130)x54x3-6x9-10. In terms of runtime, GRASP solved every instance in less than one second.

Table 4 depicts the total ergonomic strain caused by the non-optimized default stowage plan in column “primary value” and the relative improvement of the optimal solution as reported by DP in the column “impr.”. According to our tests, if the tow train is loaded to its maximum capacity, optimizing the bin stowage yields an averaged ergonomic improvement of about 11%. In the more realistic case of an 80% loaded tow train, optimizing the bin placement improves the average ergonomic assessment by between about 10% to about 14% on average, depending on the instance size. Taking into account that the economic performance of the solutions is identical (both solutions are feasible) and that no investment in any further equipment is needed, these results may be quite relevant for those practical cases where workers have to handle high loads over the course of a workday, and where they are hence exposed to an increased risk of job-related injuries.

Since our exact algorithm performs well on realistic sized instances, we further solve instances of very large size to be more of a challenge and to investigate the performance of our algorithms. The bottleneck of DP lies in partitioning bins between wagons. The number of possible partitions grows according to the Stirling number $\{\vert S\vert\}_{\vert W\vert}$. To generate two sets of very large instances, we set the value for $\vert S\vert$ to be either 16 or 24, while choosing the number of wagons $\vert W\vert$ such that the Stirling number becomes maximal for the selected value of $\vert S\vert$. We
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Table 4: Computational test on realistic sized instances for a representative male worker.
derive the values of all other parameters the same way as before. Beyond that, we again create instances with complete and 80% filling, and we generate ten instances for each value of |S| and type of filling. We solve all instances with CPLEX, DP as well as GRASP, where we use the same settings as before. The corresponding results of the computational experiment are summarized in Table 5.

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<td>x63x3-7x16-09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>XL-m-189</td>
<td>x63x3-7x16-10</td>
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<td></td>
</tr>
<tr>
<td>mean</td>
<td>238.49</td>
<td>11.53</td>
<td>211.01</td>
</tr>
</tbody>
</table>

* in comparison to the best found objective value (instead of the known optimum)

n.k. = not known

Table 5: Computational test on very large instances.

CPLEX is able to find feasible solutions for all instances with 16 stations (labeled XL) and instances with 24 stations (labeled XXL), provided the tow train is only loaded to 80% capacity. However, only three instance are proven to be optimal within the time limit of 3600 seconds, and there is a positive optimality gap in two instances (although the optimality gaps are below 0.1% in both cases). For all XL and XXL instances where the tow train is filled completely, except for instance XL-m-189(189)x63x3-7x16-06, CPLEX is not able to find feasible solutions at all within the set maximum runtime.

DP is able to find the optimal solution for all XL instances within a runtime of at most 135 seconds. All XL instances without “ghost” bins can still be solved within a runtime of less than a tenth of a second. Contrarily, DP starts to struggle if the tow train is only filled to 80% capacity with bins, needing an average of 27 seconds. This is due to the fact that there is a much larger number of feasible partitions of bins to wagons in the 80% filled instances than in the completely filled ones. In the case of the XXL instances, DP is only able to solve the completely filled instances, but fails to find solutions for 80% instances within the time limit of 3600 seconds.

GRASP, on the other hand, is able to find solutions for all of the very large instances. The relative optimality
gap never exceeds 0.3\% for the completely loaded instances. For the 80\% filled XL instances, the optimality gap is slightly higher at 0.6\% on average, while it is approximately 0.7\% for the 80\% filled XXL instances. Interestingly, the behavior of the runtime of GRASP turns out to be somewhat the opposite of dynamic programming. While its runtime is generally low (never exceeding 3 seconds, even for the hardest instances), GRASP is quicker at solving the 80\% filled instances. This is most likely due to the fact that randomly generated initial solutions are more likely to be feasible if the tow train is not filled completely. This saves time needed for repairing and therefore boosts the performance of GRASP.

Finally, we compare the achieved relative improvement in total ergonomic strain for two types of instances, one were the anthropometric measurements of a representative male worker and another one where the anthropometric measurements of a representative female worker were used for the ergonomic evaluation (cf., Section 5.1.2). The results are summarized in Table 6, which depicts the mean relative improvement (between the primary and optimal objective) for every class of instances for both, the representative male as well as female worker. Depending on the assumed worker, relative improvements only vary by a few tenths of a percentage point (at most by 0.62 percentage points) for each instance class, even though the anthropometrics of both workers differ significantly. For most instance classes, the difference in relative improvements is even below a tenth of a percentage point. The main purpose of this comparison is to demonstrate that relative improvements in total ergonomic strains are roughly independent of the worker’s assumed anthropometric measurements. Hence, this comparison suggests that the implications derived in our computational study – like, for example, the amount of improvement that can be expected by (un-)loading tow trains ergonomically – are valid for a broad spectrum of practical cases with varying workers.

$$\begin{array}{cccccc}
\text{instances} & \text{mean rel. impr. male} & \text{mean rel. impr. female} & \text{instances} & \text{mean rel. impr. male} & \text{mean rel. impr. female} \\
\text{(in \%)} & \text{(in \%)} & \text{(in \%)} & \text{(in \%)} & \text{(in \%)} & \text{(in \%)} \\
S-\#-54(54)x18x3-2x3-## & 11.20 & 11.15 & XXL-\#-243(194)x81x3-9x24-## & 16.29 & 16.26 \\
S-\#-54(43)x18x3-2x3-## & 9.78 & 9.71 & M-\#-108(86)x36x3-4x6-## & 11.54 & 11.49 \\
M-\#-108(86)x36x3-4x6-## & 14.36 & 14.27 & M-\#-108(86)x27x4-3x6-## & 11.12 & 11.07 \\
L-\#-162(162)x54x3-6x9-## & 13.99 & 13.83 & (1 \text{ extra rack per wagon}) & 1.55 & 1.60 \\
L-\#-162(130)x54x3-6x9-## & 11.53 & 11.47 & M-\#-108(86)x36x3-5x6-## & 14.45 & 14.45 \\
XL-\#-189(189)x63x3-7x16-## & 11.73 & 11.68 & (1 \text{ extra slots per rack}) & M-\#-135(86)x45x3-5x6-## & 1.55 & 1.59 \\
XL-\#-189(151)x63x3-7x16-## & 11.73 & 11.68 & (1 \text{ extra wagon}) & \\
XXL-\#-243(243)x81x3-9x24-## & & & \\
\end{array}$$

Table 6: Comparison of achieved relative reductions in ergonomic strains for a representative male and female worker.

### 5.2.2. Influence of different tow train designs, set-ups and managerial decisions

This section takes a closer look at how the total ergonomic strain of a tow train is influenced by its design and by managerial decisions. As a first experiment to attain some design insights, we compare reference instances to instances we derive by varying different parameters that define the tow train’s set-up. All other parameters, such as bin weights, for example, stay unchanged. The results of our study are summarized in Table 7.

Our reference instances are the M-m-108(86)x36x3-4x6-## instances we also use in our computational performance study, because those instances can be considered the most representative for industrial practice. To briefly recap, the tow train these instances are modeled on has four wagons. Each wagon has three different shelves, each holding three slots. Each slots has a capacity of $\mu = 3$. Overall the tow train can carry up to $n = 108$ bins, but it is only loaded up to 80\% (equaling 86 bins).

Since in practice, wagons with four shelves are quite common, we first investigate how four-shelved wagons compare to the three-shelved ones of our reference instances. To get comparable results, we set the shelf
<table>
<thead>
<tr>
<th>instances</th>
<th>results</th>
<th>abs. impr.</th>
<th>rel. impr. (in %)</th>
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<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>M-mm-108(86)x36x3-4x6-10 reference</td>
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<td>0.00</td>
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<td>8.83</td>
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<td>7.87</td>
<td>8.27</td>
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<td>1.24</td>
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<td>1.08</td>
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<td>1.97</td>
<td>2.13</td>
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<tr>
<td>mean</td>
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<td>0.92</td>
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<td>M-mm-108(86)x36x3-3x6-05 1 extra slots per rack</td>
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<td>M-mm-108(86)x36x3-3x6-06 1 extra slots per rack</td>
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<td>M-mm-108(86)x36x3-3x6-07 1 extra slots per rack</td>
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<td>1.44</td>
<td>1.55</td>
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</tbody>
</table>

Table 7: Computational test on varying tow train set-ups.
heights of our four-shelved instances to be in the same realm as the shelf heights of our three-shelved ones, which results in shelf heights of 30 cm, 75 cm, 120 cm and 165 cm. Furthermore, since increasing the number of shelves by one increases the capacity of each wagon by nine, we reduce the number of wagons per tow train by one, so that the tow train has the same overall capacity.

The results in Table 7 suggest that it is ergonomically advantageous to use wagons with four shelves, since on average, they cause about 8.3% less ergonomic strain. This is most likely due to the fact that there is more space on shelves of medium height, which enable the worker to pick bins at lower energy expenditure levels. Beyond that, tow trains with four-shelved wagons may offer an additional advantage in practice: since they are generally shorter, they are better suited if space is scarce and paths are narrow.

Our next experiment regards the capacity $\mu$ of each slot. By broadening the wagon, and therefore each shelf, it is possible to increase $\mu$. While in our reference instances, we have set $\mu = 3$, a slot capacity of four is also reasonable. We therefore create instances, again based on our reference instances, with an increased slot capacity of $\mu = 4$. This increases each wagons’ capacity by nine bins, which is why we again shorten the tow train by one wagon to maintain the same overall capacity. All other parameters remain unchanged.

The results depicted in Table 7 show that increasing $\mu$ might be beneficial from an ergonomic perspective, but only slightly, since the objective was only improved by about 1.6%. By increasing $\mu$ and reducing $|W|$ as described, the amount of space on shelves of a specific height stays constant. This implies that only the altered way of partitioning bins to wagons can influence the objective value. As our results show, this influence is quite low.

Next, we investigate how the total ergonomic strain is influenced by the number of slots on each shelf. Again, starting from our reference instances, we create new instances by adding an additional slot per shelf, i.e., making the wagons longer. As before, we again shorten the tow train by one wagon to retain the same total capacity.

The results of this experiment are shown in Table 7. They mirror the results of the previous experiment, which is not coincidental: Increasing the slot depth and lengthening the wagons both add the same number of additional slots to each shelf level. Therefore, both kinds of altered instances yield the same change of the optimal objective value.

Finally, we investigate how the relative filling of the tow train influences total ergonomic strain. Clearly, loading fewer bins on a tow train reduces the total ergonomic strain for (un-)loading. However, assuming line-side demands stay unchanged, tow trains that are loaded to a lesser degree have to execute delivery cycles more frequently to fulfill demands. Similar trade-offs have already been reported in the literature with the objective of minimizing line-side stocks (cf. Section 2), where more frequent smaller lot deliveries prove to be advantageous (cf., Emde et al., 2012).

To assess the effects of this tradeoff on ergonomics, we conduct the following experiment. We begin with an instance of a completely filled tow train and solve it to optimality. The result is used as a reference in the subsequent evaluation. In the next step we reduce the tow train’s filling by a relative amount $\Phi$ by deleting $(1 - \Phi) \cdot n$ bins (i.e., we transform them into “dummy” bins) from the respective instance, while we keep the bin distribution regarding destined stations and weights as similar as possible. We solve the modified instance to optimality and calculate an adjustment factor $\frac{1}{\Phi}$, which denotes how much more frequent the tow train of the modified instance needs to execute delivery runs compared to the reference instance’s tow train. We then multiply the optimal objective value of the modified instance by the adjustment factor and divide the product.
by the objective value of the reference instance. This yields an index that compares the ergonomic strain of the modified instance and the reference instance. We acknowledge that this experiment is based on quite restrictive assumptions, for example, that the number of tow trains, their capacity and their assigned drivers are fixed. We further do not account for the fact, that decreasing the filling of a tow train by a certain amount reduces the time to complete a delivery cycle only by a sub-proportional time span, which leads to infeasible schedules for low fillings. Nevertheless, our experiment can provide some valuable insight into how just-in-time lean production strategies, which emphasize more frequent small lot deliveries, influence ergonomics.

We evaluated all small-, medium- and large-sized instances with the described procedure for different values of \( \Phi = \{ \frac{1}{9}, \frac{2}{9}, \ldots, \frac{9}{9} \} \). The averaged results are depicted in Figure 5.

![Figure 5: Influence of tow train filling on total ergonomic strain.](image)

Independent of the instance size, Figure 5 shows some clear trends. Between \( \Phi = \frac{1}{9} \) and \( \Phi = \frac{3}{9} \), the index of the total ergonomic strain stays approximately constant. Afterwards, between \( \Phi = \frac{3}{9} \) and \( \Phi = 1 \), the index of the adjusted total ergonomic strain increases with increasing tow train filling. The trend is linear in good approximation, although there might be a (debatable) slight change of gradient at \( \Phi = \frac{6}{9} \). We explain this trend as follows. If the tow train is filled to a high degree, all ergonomically advantageous places are occupied by bins, such that the remaining bins are forced to be stored on ergonomically disadvantages rack heights. Reducing the filling of the tow train decreases the amount of bins that are forced to be stored on the latter. Hence, even though the tow train needs to deliver more often, the total amount of bins, which are transported (and, hence, (un-)loaded) on ergonomically disadvantageous racks, decreases. Once the tow train is filled to a degree of \( \Phi = \frac{2}{9} \) or less, storage space is sufficient to store all bins on the ideal rack height (since there are only three different rack heights at our instances’ tow trains), which explains why the decreasing trend becomes approximately constant. Deviations from this trend, which are more pronounced the less the tow train is filled, are due to our experimental design: the less the tow train is filled, the less accurate we are able mirror the primary distribution, which causes some disturbances. Note that filling the tow train to such low degrees is unlikely to be feasible (or at least desirable) in most practical situation. In conclusion, the results suggest that lean production strategies – which are often implemented where tow trains are deployed – can have positive effects on the reduction of ergonomic strains.
6. Conclusion

In this paper we consider the novel problem of improving the stowage of bins on tow trains from an ergonomic point of view without worsening its economical performance. We formalize this problem as a MIP model and prove that finding feasible solutions is NP-hard.

We decompose the problem into two sub-problems: first a partitioning problem, and, second, an assignment problem. While the assignment problem can be efficiently solved, the partitioning step is a bottleneck. We develop two solution procedures, an exact dynamic programming algorithm as well as a heuristic solution procedure embedded in a GRASP framework, both using the problem’s decomposability. Computational tests show that our dynamic programming procedure is able to solve instances of realistic size within a runtime of below a tenth of a second. The GRASP-based heuristic procedure performs well, especially on very large instances. Optimality gaps are below 1% in nearly all cases and the runtime never exceeds 3 seconds.

We further derive the following take-home conclusions from a managerial point of view.

- Total ergonomic strain can be lessened, in our examples by up to about 14%, by simply optimizing bin stowage.
- From a design perspective, tow train wagons with more racks seem to be advantageous, as they offer more storage capacity at easy-to-access heights. By comparing two kinds of tow trains, one with three racks per wagons and one with four racks, both having the same overall loading capacity, the latter allowed for optimal stowage plans causing on average 8.4% less total ergonomic strain compared to the former.
- As a further design issue, we found that increasing each wagon’s capacity by broadening or lengthening it allows for the reduction of the total amount of wagons per tow train without worsening the ergonomics. In fact, in our tests, optimal total ergonomic strains even slightly decreased by about 1% on average.
- Decreasing a tow trains relative filling while increasing its delivery frequency reduces total ergonomic strain. Hence, high-frequency small-lot delivery strategies, which are emphasized in lean production concepts, are also advantageous from an ergonomic perspective.

Future research may aim to refine or validate the ergonomic evaluation method we use to assess (un-)loading tow trains. This can either be done by using alternative ergonomic assessment methods – a biomechanical approach, for example – or via actual field measurements. In addition, research might try to quantify the health benefits of stowing bins on a tow train in an ergonomic manner, possibly by means of a case study.

For additional managerial insights, assessing the weight distribution of bins may be of interest to conclude if it is beneficial to fill bins in a way that ensures equal weights, or if an unequal distribution offers ergonomic advantages.

Regarding the mathematical model, alternative objectives may be considered. One possibility is to minimize the maximum sum of ergonomic strains per station if the tow train is unloaded by the worker at the respective stations. Another option is to minimize the maximum ergonomic strain, which aims to prevent overload injuries from (un-)loading especially heavy bins. Further, it is possible to investigate additional conditions, like, for example, a given inbound sequence of bins that has to be taken account of.
A. Appendix

Figure 6: Schematic sequence of tasks to load a tow train wagon.

Figure 7: Schematic sequence of tasks to unload a tow train wagon.

References


