REDUCING WORKLOAD IMBALANCE IN PARALLEL ZONE ORDER PICKING SYSTEMS

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ABSTRACT
To stay competitive and preserve high service levels for their customers, the focus of warehouses in today's supply chain is on timely and faster delivery of smaller and more frequent orders. To keep up with competitors, companies accept late orders from customers, which results in additional pressure for order picking operations. Specifically, more orders need to be picked and sorted in shorter and more flexible time windows, which often results in workload peaks during the day. The objective of this study is to balance the workload across the day in parallel zone order picking systems. A real-life case-study demonstrates the value of balancing the workload for European order lines in a large international warehouse system located in Belgium, engaged in the distribution of spare parts. Solving the operational workload imbalance problem results in a more stable order picking process and overall productivity improvements for the total warehouse operations.

Keywords: warehouse planning, manual order picking, workload balancing, integer programming

1. INTRODUCTION

To stay competitive, companies try to minimise logistical costs as they play an important role in the total cost of a product (Rouwenhorst et al. 2000). Warehouses, where products can be stored before the fulfilment of customer orders, play a vital role in the supply chain, and costs can be cut by organizing warehouse operations in an efficient and effective way (Davarzani and Norrman 2015).
To be able to fulfil customer orders, warehouse operations need to satisfy basic requirements such as receiving, storing and retrieving stock keeping units. Sometimes value added activities such as labelling and kitting are performed before the retrieved goods are assembled for shipment. Many design and operation challenges need to be considered and carefully implemented in order to meet capacity, throughput and customer service requirements (Gu et al. 2007).
Of the four main warehouse activities (receiving, storage, order picking and shipping), order picking is the most costly. Up to 50% of the total warehouse operating costs can be attributed to this activity (De Koster et al. 2007). Order picking, where goods are retrieved from storage or buffer areas to fulfil incoming customer orders, tends to be very labour intensive when it is done manually, and very capital intensive when automated warehouse systems are used (Gu et al. 2007).
Although automating the order picking process is possible, the most popular order picking system in practice is still the low-level, picker-to-parts order picking system. About 80% of all order processes are performed manually, because human operators are considered to be more flexible if unexpected changes occur in the process. Despite its popularity in practice, most research efforts have been performed in areas of AS/RS, focusing on high-level picking rather than its manual counterpart (De Koster et al. 2007).
Besides the continuous focus on reducing logistical costs, trends such as shortened product life cycles, e-commerce, greater product variety and point-of-use delivery expose warehouse management to new challenges. To overcome these challenges and simultaneously preserve high service levels, warehouses need to be able to fulfil many small orders for a great variety of stock keeping units (SKUs) (Davarzani and Norrman 2015).
Furthermore, to stay competitive, companies are accepting late orders from customers. This results in extra difficulties for planning order picking operations: more orders need to be picked and sorted in shorter and more flexible time windows. To fit these limited time windows, order picking time needs to be reduced, as this is an integral part of the delivery lead time (De Koster et al. 2007).
Apart from reductions in order picking times, other possibilities exist to keep up with competition and to fulfil imposed service levels. Nowadays the order picking process is expected to be flexible and in the meanwhile customer orders need to be fulfilled in a timely and efficient manner, despite limited time windows. Because of this trend, warehouse managers and supervisors experience difficulties in balancing the workload of the order pickers on a daily basis, resulting in peaks of workload during the day. These workload imbalances result in order picking inefficiencies as order pickers need to cope with high peaks in demand, forced by certain departure deadlines of shipping trucks.
The focus of this paper is on the minimization of the hourly variation of the workload during the day, which is

highly relevant for practitioners. The balancing of workloads results in a more efficient picking process, and will cause higher utilization rates of the available workforce, resulting in a better performance and efficiency of the overall warehouse operations.
The remainder of this paper is organized as follows. Section 2 provides a discussion on related literature. The new operational workload imbalance problem is introduced and described in Section 3. Section 4 is devoted to the results and summarizes managerial implications of this study. Section 5 concludes the paper.

2. LITERATURE REVIEW

To optimize the challenging process of order picking, various planning issues have been identified in the literature: layout design, storage assignment, order batching, zoning, picker routing and to a lesser extent workforce scheduling (De Koster et al. 2007). The zoning problem and the problem of workforce scheduling are most related to the problem of workload imbalance, as both planning problems substantially impact workload peaks. Managing the zoning problem should prevent workload imbalance across order picking zones, whereas workforce scheduling should prevent workload imbalance between order pickers. Related literature, focussing on each of these planning problems, is discussed below.
A well-known tactical option to lift order picking performance to a higher level is the division of the warehouse into different zones. Zone picking assigns the order picker to a dedicated zone. The order picker only picks items of an order that are located in his or her zone (Petersen 2002). Research focussing on zoning is divided into two types of zoning: parallel (or synchronized) zoning and progressive zoning. In synchronised zoning, all zone pickers work on the same batch of orders, while in progressive zoning, a batch of orders is sequentially passed from one zone to the other (Yu and De Koster 2009).
Zoning leads to several advantages. First of all, the picker traverses smaller areas in the warehouse, which leads to travel distance reduction. Furthermore, order pickers become familiar with the item locations in the zone they are assigned to. The biggest disadvantage associated with zoning is the need for consolidation before shipment, because orders have been split during the zoning process (De Koster et al. 2007). Furthermore, labour and equipment resources need to be allocated across the different zones in the warehouse (Gu et al. 2007).
Jane (2000) smoothens a serial pick lane by balancing workloads in such a way that the difference between the number of picks of each order picker is minimized. The effect of adding or deleting storage zones during slack and peak periods is analysed. Jane and Laih (2005) consider a parallel zoned manual order picking system and develop a heuristic algorithm to balance the workload among order pickers by analysing different assignments of products to order picking zones. Despite the valuable contribution of these papers to balance the workload among zones in the long run, these solution methods will be less suitable in an operational context, where daily operations need to be planned and managed. Another way to safeguard customer service against peaks in workload is efficient scheduling and staffing of the order picking personnel. This personnel planning problem is a commonly formulated research opportunity in warehouse literature. A large number of workforce related studies have been conducted in manufacturing environments (De Bruecker et al. 2015; Xu et al. 2011), but similar studies in warehousing are rather limited (Davarzani and Norrman 2015; Rouwenhorst et al. 2000).
Due to several differences between warehouses and manufacturing environments, the results obtained in both environments cannot be assumed to be equal. Efficient employability of human resources is necessary because of the labour intensive nature of warehousing operations. Warehouses have to deal with strong fluctuations in daily demand and should simultaneously be able to meet fixed deadlines in short time intervals. To face these challenges, warehouses need to be highly flexible (Van Gils et al. 2016).
An important aspect of the personnel scheduling problems is deciding on the number of employees needed to cover the workload. Adaptations in the labour force can be used to cope with fluctuations in demand (Van den Bergh et al. 2013). Temporary workers are often hired in order to capture workload peaks between different days (Grosse et al. 2013). Personnel capacity is an important driver in the service quality companies are able to deliver to their customers (Defraeye and Van Nieuwenhuyse 2016). On the one hand, an insufficient number of workers reduces the service level. On the other hand, planning too many workers will cause unnecessarily high labour costs, congestion in the warehouse, and falling picking efficiency (Van Gils et al. 2016).
Four steps in the personnel planning process have been determined in literature. The first one is demand forecasting. The second step is the determination of staffing requirements to meet certain goals or avoid certain costs over time. Thirdly, shift scheduling is necessary in order to meet the staffing requirements. Shift scheduling results in deciding how many workers are needed in evert shift type. In a fourth step, employees are assigned to shifts, which is called rostering (Defraeye and Van Nieuwenhuyse 2016).
The solution to the problem that is tackled in this paper is most related to the third step in the personnel planning process. Balancing the workload by a minimization of the hourly variation in order lines, will result in a reduction of temporary, more expensive order pickers which were needed to be able to process peaks in workload. Likewise, it will become easier to plan the number of required order pickers for every zone.
To conclude this section, the focus of this paper is on the minimization of the hourly variation of the workload in a parallel zoned manual order picking system. Balancing the workload in an order picking system can be addressed from different perspectives. While most papers that

cover the issue of workload imbalance, start at a strategic or tactical level, the emphasis of this paper will be on the operational level, to avoid peaks in the number of orders to be picked in certain time slots during the day. To the best of our knowledge, we are the first to focus on workload peaks during the day. The objective of this paper is therefore to minimize variations in workloads per time slot by assigning order sets to a single time slot, conducted for every zone. This warehouse planning problem is defined as the operational workload imbalance problem.

3. OPERATIONAL WORKLOAD IMBALANCE PROBLEM

The operational workload imbalance problem will be introduced in section 3.1, in the context of the company used in the case-study. Section 3.2 discusses the mathematical formulation of the new problem.

3.1. Problem Description

The warehouse studied in this paper is a large international B2B warehouse located in Belgium. The warehouse is responsible for the storage of automotive spare parts and the distribution of these parts around the globe. The mission of the company is to maximize the operating time of their sold vehicles by aiming at fast throughput times and reliable deliveries.

The warehouse under consideration is fully manually operated and is divided in several zones, as can be observed in Figure 1. The products have been assigned to the different zones based on their dimensions, weights or demand patterns. This division is necessary because different handling methods are used for products with different dimensions.

Zone one is divided into three parts: A, B and C. Products with the highest demand are located in the A part of zone one, while products with the lowest demand are situated in part C. Products in zone two are characterised by their small size. Products are stored in plastic boxes which contain for example small buttons and screws. The third zone contains products that are heavier than 15 kilograms or contain products that do not fit standard euro pallet measurements. Products that are demanded most of all goods in the warehouse can be found in zone four. Zone five contains all products that are already packed individually for shipment. This study will only consider the zones marked in grey in Figure 1.

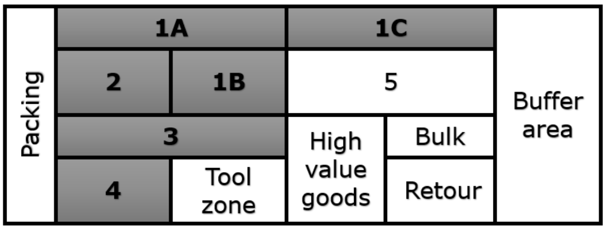

Figure 1: Warehouse Layout

Spare part warehouses are characterized by orders that can be grouped based on their destination. An order set refers to a group of orders with a common destination that is picked in a single zone. Deadlines of customer orders are determined by the shipping destination and resulting schedule of shipping trucks (i.e. shipping schedule). Each shipping truck can consist of multiple order sets (i.e. a single order set for each order picking zone). The assignment of orders to shipping trucks as well as the shipping schedule are assumed to be fixed at the operational level. The fixed shipping schedule often results in workload peaks during the day, as order patterns vary across customers and destinations (e.g. varying number of orders and customers, varying order point and resulting available time to pick orders). The release time of an order set is fixed at the point in time that 95% of the orders belonging to each order set have been send to the warehouse, based on real-life order data of two years.

In this paper, we introduce a new mathematical programming model describing the operational workload imbalance problem in a parallel zoned manual order picking system. The operational workload imbalance problem assumes that the number of order pickers in each shift is equal in each order picker zone.

3.2. Problem Formulation

This section introduces and discusses the new mathematical formulation of the operational workload imbalance problem with the aim of reducing workload imbalance in parallel zone order picking systems. To formulate the problem, following notations are used:

<u>Sets</u>

I	Set of time slots with time slot $i \in I$
J	Set of shipping trucks with $j \in J$
K	Set of pick zones with $k \in K$

<u>Decision variables and Parameters</u>

a_{jk}	Average number of order lines for shipping truck j in zone k
t_i	Time slot i
Δt_{max}	Maximum difference in number of time slots that is allowed for planning order sets of a single shipping truck over different zones.
X_{ijk}	Binary variable which is 1 if shipping truck j in zone k is planned in time slot i
$t_{release,\,j}$	Release time for orders of shipping trucks j
$t_{deadline,\,j}$	Order picking deadline orders of shipping trucks j
Max_k	Maximum number of order lines in zone k
Min_k	Minimum number of order lines in zone k
δ	Split order set factor

Subsequently, the objective function and associated constraints are discussed for the operational workload imbalance problem. This study formulates the problem as a mathematical programming problem and aims to solve the problem to optimality using CPLEX. The minimization of the range for workload deviation in every zone on a particular day of the week is considered as objective function. In other words, the difference between the maximum and minimum number of order lines per time slot is minimized for every zone.

$$MIN \sum_{k=1}^{K} (Max_k - Min_k) \quad (1)$$

The model is subject to the following constraints:

$$\sum_{i=1}^{I} t_i X_{ijk} \geq t_{release,j} \quad (2)$$
$$\forall\ k = 1 \dots K, \forall\ j = 1 \dots J$$

$$\sum_{i=1}^{I} t_i X_{ijk} \leq t_{deadline,j} \quad (3)$$
$$\forall\ k = 1 \dots K, \forall\ j = 1 \dots J$$

$$\sum_{i=1}^{I} X_{ijk} = 1 \quad (4)$$
$$\forall\ k = 1 \dots K, \forall\ j = 1 \dots J$$

$$Max_k \geq \sum_{j=1}^{J} a_{jk} X_{ijk} \quad (5)$$
$$\forall\ k = 1 \dots K, \forall\ i = 1 \dots I$$

$$Min_k \geq \sum_{j=1}^{J} a_{jk} X_{ijk} \quad (6)$$
$$\forall\ k = 1 \dots K, \forall\ i = 1 \dots I$$

$$\sum_{i=1}^{I} t_i X_{ijk1} - \sum_{i=1}^{I} t_i X_{ijk2} \leq \Delta t_{max} \quad (7)$$
$$\forall\ j = 1 \dots J,$$
$$\forall\ k_1 = 1 \dots K, \forall\ k_2 = 1 \dots K,$$
$$k_1 \neq k_2$$

Constraints (2) indicate that the release time of an order set needs to be smaller or equal than the time slot that orders will be released. Similarly, constraints (3) indicate that pick deadline of an order set is larger than the scheduled time slot. Assigning each order set to a single time slot is the result of constraints (4). Constraints (5) and (6) define the maximum and minimum number of order lines over all time slots for every zone. Constraints (7) incorporate the allowed difference in time slots for planning order lines of a certain shipping truck over different zones. This difference in time slots cannot exceed a certain parameter Δt_{max}.
Besides aforementioned constraints, the model will take into account an extra parameter δ in case extreme large order sets occur for planning. The split order set factor δ is defined as the fraction of the mean number of order lines per time slot in zone *k*. The split order set factor results in an extra set of constraints:

$$a_{jk} \geq \delta \mu_k \quad (8)$$
$$\forall\ j = 1 \dots J,$$
$$\forall\ k = 1 \dots K$$

By means of the size of *δ*, the order sets will be split into two if an order set of a shipping truck *j* is greater than *δ* times the mean number of order lines in zone *k* in order to facilitate balancing over the different time. Furthermore, the split order sets must be planned in consecutive time slots.

4. RESULTS AND DISCUSSION

Section 4.1 is devoted to the experimental design. Section 4.2 describes the results and discusses the findings. Section 4.3 provides some important managerial implications.

4.1. Experimental Design

The operational workload imbalance problem aims at reducing the workload imbalance during the day in a parallel zoned manual order picking system. The factors and their associated factor levels for the experiment of this paper are summarized in Table 1. The first factor in the experiment is Δt_{max}, and is tested at four different levels. The second factor is the split order set factor *δ* and includes four levels as well. This factorial setting results in a 4 x 4 full factorial design. Each factor level combination is replicated for each day of the working week (Mon – Fri), resulting in 80 observations.

Table 1: Experimental Factor Setting

Factors	Factor levels			
Δt_{max}	1	2	12	25
δ	1	1.25	1.5	∞

The size of Δt_{max} is of practical relevance, as this influences usable space in the staging area of a company. In the most extreme case, Δt_{max} has a value of 25. As the number of time slots is limited to 24, constraints (7) are no longer binding and order sets can be planned, without taking into account the time slot of order sets for the same destination planned in other zones. This can result in overcrowded staging areas when order sets for same destinations originating from different zones have to wait for each other. The smaller the staging area of a company, the better it would be to keep Δt_{max} small, as waiting times for order sets of same destinations will be lower.
The order set factor *δ* ensures a better balanced solution as large order sets are split in half when they exceed a certain fraction of the average number of order lines per time slot in a zone. Parameter *δ* takes values from one to infinity. If *δ* takes the value of one, order sets are split if they are larger than the average order size in the corresponding zone. When *δ* is set to infinity, no orders will be split, which means that large order sets have to be planned in a single time slot.

4.2. Computational Results

The experimental factor levels are simulated by solving the operational workload imbalance problem using CPLEX with a time limit of six hours for all instances. Considering 80 instances, none are solved to optimality. The optimality gap varies between 0.916% and 37.852% with an average of 10.346%. The objective value ranges from 215.59 to 1,396.32, with an average of 528.26. In the remainder of this section, the effect of Δt_{max} and *δ* is studied on both the objective function value and the size of the optimality gap.
Figure 2 presents the effect of the different levels of Δt_{max} and *δ* on the mean objective function value. The graph indicates no existence of an interaction between both factors. For the split order set factor *δ*, it becomes clear that for *δ* = ∞, the mean objective function value is

highest for all levels of Δt_{max}. This result can be expected as $\delta = \infty$ means that no order set can be split over multiple time slots. Balancing the workload becomes hard in this situation, as the largest order set defines the maximum peak that cannot be further reduced. The other levels of factor δ result in substantially lower objective function values, because large order sets can be divided over multiple time slots. If $\delta = 1$, which means orders are split in half whenever they are larger than the average number of order lines in a zone, the lowest workload range is reached.

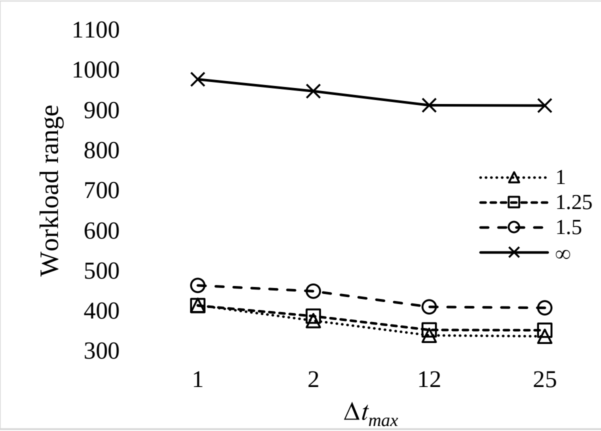

Figure 2: Interaction Plot for Average Workload Range

For the factor of Δt_{max}, a slight downward trend can be observed from Figure 2, indicating that there are more possibilities for reducing the range when constraints (7) are no longer binding.

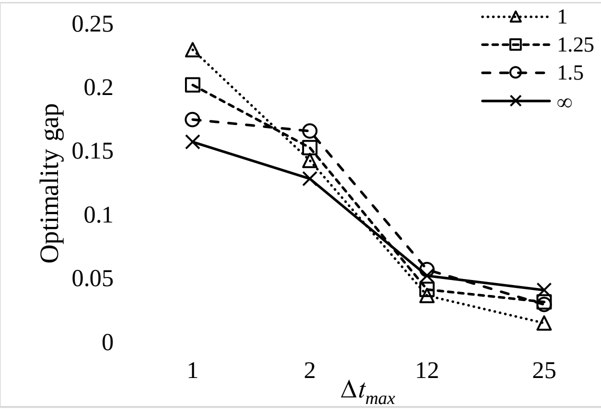

Figure 3: Interaction Plot for Average Optimality Gap

As illustrated in Figure 3, the difference in optimality gap is mainly due to the factor Δt_{max}. Given a specific level of Δt_{max}, different levels of the split order set factor result in only small differences in mean values for the optimality gap. Whenever Δt_{max} has a value of 25, order sets can be planned in all available time slots before their deadline, as the planning does not have to consider the planned order sets for same shipping trucks in the remaining zones. In other words, the planning in each zone is independent, which seems to result in smaller optimality gaps.

If a decision has to be made on the value of Δt_{max}, not only aforementioned results need to be taken into consideration. As already stated, Δt_{max} influences the space that is left in the staging are. The choice will strongly depend on the size of the staging area of the warehouse under consideration. Table 2 illustrates the difference in space utilization in the staging area expressed in number of shipping trucks and corresponding number of order lines for $\Delta t_{max} = 1$ and $\Delta t_{max} = 25$. For every option, the minimum and maximum number of shipping trucks and order lines are calculated over all time slots that occurs on a Monday in the staging area. On average when Δt_{max} is set to 25, place has to be reserved for 2,219.67 extra order lines in comparison to the situation where factor Δt_{max} is fixed at level one.

Table 2: Occupation of the Staging Area

Summary	$\Delta t_{max} = 1$	$\Delta t_{max} = 25$
min # shipping trucks	13	11
max # shipping trucks	48	56
average # shipping trucks	32.88	34.54
min # order lines	1,432.80	3,887.67
max # order lines	8,077.98	11,839.04
average # order lines	4,899.05	7,118.72

4.3. Managerial implications

If peaks in the workload are observed during the day, it is possible that the required order throughput exceeds the capacity of the available order pickers at certain points within their shift. This results in missed departure deadlines and lower customer satisfaction. The operational workload imbalance model developed in this paper tries to minimize this hourly variation of the workload on each day. This is highly relevant for practitioners to construct a more stable order picking process, which ultimately results in more efficient warehouse operations.

This section discusses the practical implications of this research for warehouse managers and supervisors. First of all, the problems of the current pick plan and its deadlines are examined for the warehouse described in Section 3.1. Subsequently, the balanced workload solution calculated by the model is graphically displayed, and its benefits and implications are discussed.

The order picking deadlines for the given shipping schedule of the Belgian warehouse can be observed in Figure 4. As an example, shipping deadlines and corresponding order lines for every order set in zone 1 are shown for a Monday. Time slot one corresponds to the time interval 21 p.m.-22 p.m.

In the current situation, order pickers gradually pick orders that enter the system, with a priority given to order sets with pressing deadlines (i.e. earliest-due-time). As shown in Figure 4, shipping deadlines for order sets are not equally divided over all time slots. No shipping deadlines exist during night (time slot 1 to 6), while more departures pile up during the day. This means more

deadlines need to be met and the order picking system is subject to peaks in workload during daily hours.
Every day, a rough estimate is made of the total number of order lines that need to be picked the next working day, and at the same time the total amount of picked order lines for every zone is guessed. If peaks occur in certain time slots, that cannot be covered by the order pickers who are present, warehouse supervisors carry out a last minute assignment of employees of other warehouse activities to the different zones in need. The number of people and the assignment to zones is based on their experience. Using other warehouse employees for covering peaks in order picking workload, results in inefficiencies in the corresponding activities. Sometimes these other activities are delayed or even shut down.

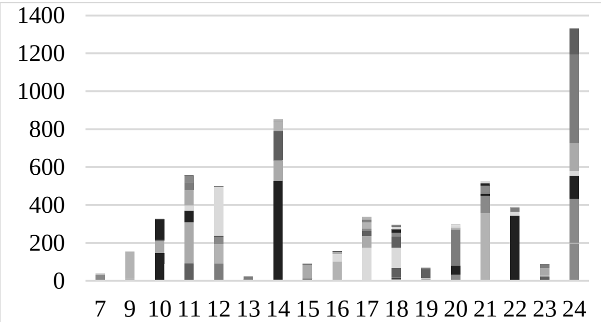

Figure 4: Current Deadlines Belgian Warehouse with each Block Representing a Single Order Set

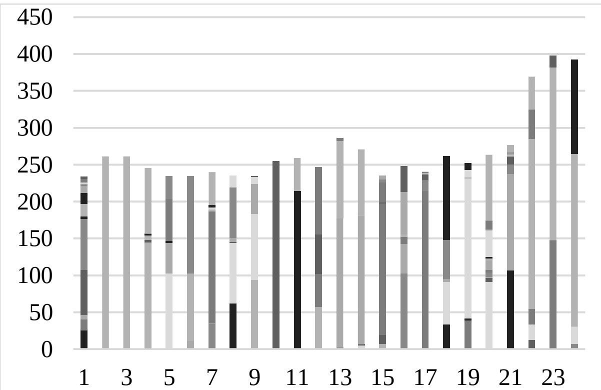

Figure 5: Balanced Planning with each Block Representing a Single Order Set

The operational workload imbalance model developed in this paper provides a solution for abovementioned problems. Figure 5 presents the results of the model with respect to Monday. Factor Δt_{max}, as well as the split order set factor δ are fixed at their second level of the experimental design. These levels are considered as the best fitting values to the real-life warehouse operations of the case-study.
By balancing the workload, as can be observed in Figure 5, the order picking process can be kept under control. In other words, for every time slot, certain goals are set for picking predefined order sets. This way, warehouse supervisors are better prepared and can check at every moment in time if they are on schedule. If not, warehouse supervisors are able to intervene timely, without disturbing other warehouse employees and processes, as is the case in the current situation.
With respect to the balanced planning shown in Figure 5, the graph shows an increased number of order lines in the last three time slots. In order to decrease this imbalance, we proposed to shift the release of a single shipping truck j^* from time slot 22 to time slot 21. This means that the cut-off time for customers who are delivered with shipping truck j^* is one hour prior to the current cut-off time. The operational workload imbalance model is simulated with the new release time of shipping truck j^*. Table 3 shows the results of the simulation in terms of the daily required number of full time equivalents (FTEs). Based on the average productivity, the number of FTEs is currently determined by warehouse supervisors. The minimum and maximum number of FTEs shows the minimum and maximum required number of FTEs resulting from the operational workload imbalance model as a consequence of hourly workload variations. This minimum and maximum value can be seen as an indication of the number of employees that should be shifted from other warehouse activities in order to fulfil all orders before the deadline. By only shifting a single shipping truck, the number of FTEs that should be shifted reduces significantly. For example in Zone 4, the available number of FTEs equals 10.66, while during the peak time slot 16.26 FTEs are required. This peak requirement reduces to 13.12 FTEs in case of shifting the release of shipping truck j^*.

Table 3: Daily Required Number of FTEs

	Zone 1	Zone 2	Zone 3	Zone 4
Mean productivity (in number of order lines per FTE)	33.0	8.5	63.5	38.0
Current situation (number of FTEs)				
Mean	8.12	21.72	1.41	10.66
Minimum	7.09	19.40	1.19	8.83
Maximum	12.06	27.67	2.02	16.26
Improved situation (number of FTEs)				
Mean	8.12	21.72	1.41	10.66
Minimum	7.05	20.31	1.27	9.46
Maximum	11.22	25.78	1.83	13.12

To conclude this section, several practical implications can be summarized for warehouse managers and supervisors to take into account when planning daily order picking operations. If the workload is balanced, warehouse supervisors are better prepared and other warehouse operations are less disturbed. In other words, the order picking process is less depending on individual experiences of warehouse supervisors. A better balanced workload means a better utilization rate of the order pickers in the system. By planning an evenly divided

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workload during the day, the probability of missing shipping deadlines is smaller, which results in more efficient warehouse operations.

5. CONCLUSIONS

Due to several upcoming trends in warehousing, the process of order picking is expected to keep improving in terms of flexibility, which results in shrinking time windows for order picking. Late customer order acceptance in these limited time windows causes peaks in workload during the day, resulting in extra work pressure for warehouse supervisors as well as order pickers. Until now, only solutions for long-term balancing have been introduced in literature. Practitioners were searching for a solution to balance the workload for every hour of the working day, to take their operational activities to a higher level.

This study formulates the new operational workload imbalance problem as a mathematical programming problem and tries to solve the problem to optimality using CPLEX. CPLEX has proven to be very effective in solving small planning problems (Henn and Wäscher 2012). However, mathematical programming problems can be hard to solve to optimality in reasonable computing times for planning problems of realistic size. This is supported by the results described in Section 4. Of 80 instances, none have been solved to optimality.

The novel mathematical programming model for the workload balancing problem is too complex to provide fast results. Heuristic algorithms, in particular local search based algorithms, can compensate for the risk of large computing times. Future opportunities to solve the workload balancing problem, could be the development of an iterated local search algorithm, as an example of a local search algorithm, to serve as alternative for the exact solution. Iterated local search algorithms have proven to be excellent alternatives to solve complex warehouse planning problems (Henn et al. 2010; Öncan 2015).

The developed model can be used by warehouse managers and supervisors as a simulation tool to plan order sets more accurately during the day, in this way, avoiding peaks in workload. The utilization of order pickers in the system will rise in case of a balanced pick plan. There is a smaller need for workers from other activities or expensive temporary workers to cope with peaks in demand. It is important that effects, such as necessary reserved space in the staging area, are kept in mind by setting model parameters. The developed model can also be used as an advisory tool for warehouse managers to start negotiations in changes in cut-off times for customer order entry and shipping schedules to further reduce workload imbalances.

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