Improving warehouse responsiveness by job priority management:

A European distribution centre field study

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Abstract

Warehouses employ order cut-off times to ensure sufficient time for fulfilment. To satisfy higher consumer expectations, these cut-off times are gradually postponed to improve order responsiveness. Warehouses therefore have to allocate jobs more efficiently to meet compressed response times. Priority job management by means of flow-shop models has been used mainly for manufacturing systems but can also be applied for warehouse job scheduling to accommodate tighter cut-off times. This study investigates which priority rule performs best under which circumstances. The performance of each rule is evaluated in terms of a common cost criterion that integrates the objectives of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. A real-world case study for a warehouse distribution centre of an original equipment manufacturer in consumer electronics provides the input parameters for a simulation study. The simulation outcomes validate several strategies for improved responsiveness. In particular, the critical ratio rule has the fastest flow-time and performs best for warehouse scenarios with expensive products and high labour costs.

Keywords

responsiveness; queuing model; order fulfilment; cut-off operation; flow-shop scheduling

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1. Introduction

Intense competition for speedy order fulfilment characterizes current retail markets. Responsiveness (Barclay et al., 1996) includes the ability to react purposefully within an appropriate time to external environments for securing competitive advantage. Improving order fulfilment responsiveness is a major challenge for boosting customer satisfaction (Doerr and Gue, 2013) and many firms, such as Amazon Prime, invest hefty capital to propel responsiveness. Though responsiveness hones competitiveness, it often leads to resource misallocation (T'kindt, 2011), and improved responsiveness leads for two-thirds of all firms to increased labour cost (Pearcy and Kerr, 2013). Web retailers show responsiveness by advertising 'Place an order before midnight for next-day delivery.' Customers are nowadays accustomed to such fast demand satisfaction in on-line markets and expect comparable off-line service. Off-line retailers therefore attract customers with promises like 'Buy online now and pick up in store tomorrow', forcing off-line retail distributors to improve their responsiveness (Denman, 2017).

The overall speed of order fulfilment in off-line markets depends on processing and transportation speeds from manufacturers through warehouses and retail shops to end-users. This paper focuses on speedy order fulfilment in warehouses, in particular original equipment manufacturing (OEM) warehouses delivering to retailer warehouses. Their order fulfilment process includes the inbound processes of receiving products and putting them away and the outbound processes of picking, packing, staging and shipping. As OEM warehouses receive products from their manufacturer, the inbound process is easily controlled compared to the rather unpredictable consumer demand leading to fast fluctuations of retailer orders. Another characteristic of OEM warehouses is that retailers order relatively large quantities of relatively few products (Bartholdi and Hackman, 2011). This distinguishes such warehouses from those delivering directly to consumers, where order sizes are small and range over a much wider product assortment. Whereas picking is usually the crucial stage for the latter type, in OEM warehouses the packing stage is often the most demanding one. As the receiving retailer warehouses differ in capacity and lay-out and trucks should be loaded efficiently, re-palletizing is a major task for OEM warehouses. Because of the large order volumes, the re-palletizing activities of unpacking, repacking and stacking are relatively labour intensive.

Responsiveness of OEM warehouses is measured by their flexibility to dispatch products ordered by retailers as fast as possible. To mitigate the effect of demand spikes, most OEM warehouses limit their fulfilment liability by daily order cut-off time agreements with their clients to ensure sufficient slack for order fulfilment by the earliest dispatch day (Van den Berg, 2007). To improve responsiveness, these warehouses try to postpone the cut-off time and to handle the same order volume with less slack. Since orders typically have different fulfilment deadlines, priority-based job scheduling offers the key for efficient solutions. Just as job scheduling has notably reduced waste from over-production and waiting times in “just-in-time” manufacturing, it can also improve responsiveness in warehouse order fulfilment. Job scheduling allocates tasks to labour resources for chosen goals (T’kindt and Billaut, 2006), and the question of central interest here is how OEM warehouses should schedule their orders to allow later cut-off times.

Warehouse operations are faced with various uncertainties, including dynamic arrival, service and departure times (Gong and De Koster, 2011). In particular, unexpected order arrivals can yield long delays. Because of these uncertainties there is usually no priority rule that is universally optimal (Lee et al., 1997). This paper presents a general framework for cost-effective job scheduling using flow-shop priority methods to aid warehouses facing postponed order cut-off times. This framework integrates the multiple objectives of low earliness, low tardiness, low labour idleness, and low stocks through processing lanes into a single cost criterion, with weights derived from the cost structure and performance priorities of the warehouse. A simulation study shows which scheduling methods perform best under which circumstances. The methods and results presented here advance extant literature by applying traditional flow-shop theories from manufacturing research to real-world warehouse distribution tasks. Warehouse practitioners can incorporate this task-scheduling framework in their warehouse management system (WMS) to create and execute a string of order fulfilment jobs (Van den Berg, 1999; Ramaa et al., 2012).

The rest of this paper is structured as follows. Section 2 reviews literature related to responsiveness, warehousing and flow-shop methods. Section 3 describes the operational challenge of responsive order fulfilment for postponed cut-off times. Section 4 presents the priority rules and performance indicators. Section 5 shows simulation results for the case study, and Section 6 discusses some operational implications and conclusions.

2. Literature review

We give a brief review of literature related to the main aspects of our study, i.e., responsiveness, OEM warehouses, priority-based job scheduling, and performance criteria.

Shaw et al. (2002) defined a clear hierarchy among the concepts of agility, responsiveness and flexibility. Agility concerns talents for operating 'profitably in a competitive environment of continually, and unpredictably, changing customer opportunities'. It involves both proactive initiatives and reactive responsiveness, and flexibility is one of the conditions enabling responsiveness. The study of Kritchanchai and MacCarthy (1999) identified four factors that determine responsiveness: stimuli, awareness, capabilities, and goals. In our OEM warehouse study, these factors consist respectively of hourly varying demand stimuli, awareness of demand fluctuations, job scheduling opportunities, and the goal of efficient order fulfilment.

Efficiency studies on warehouse processes focused mainly on picking strategies (Jarvis and McDowell, 1991; Hall, 1993; Petersen, 1997; Roodbergen and De Koster, 2001; Petersen et al., 2004; De Koster et al., 2007; Chen et al., 2010; De Koster et al., 2012). Proposed strategies include interleaving put-away and picking (Graves et al., 1977), wave picking (Petersen, 2000), and joint order batching (Won and Olafsson, 2005; Van Nieuwenhuyse and De Koster, 2009). The focus on picking is natural for retailer warehouses delivering directly to consumers, as such warehouses typically process large amounts of small orders for a wide variety of products by customer totes via multiple processing lines. Conversely, OEM warehouses delivering to retail warehouses process very large orders for a comparatively narrow assortment by multiple pallets via few processing lines. The outbound operations constitute a tandem queue (Burke, 1956) with three stages: picking, packing and staging. Multiple orders from the same retailer are consolidated for single shipment, which requires customized re-palletizing and packing to satisfy dimension restrictions of trucks and retailer warehouses. This makes packing by far the most labour intensive phase of the outbound process in OEM warehouses (Bartholdi and Hackman, 2011).

Consumers can nowadays easily use the internet to compare quality and prices of products across different suppliers. The offered service level remains the major competitive quality, and warehouse clients perceive responsiveness mainly by the speed of delivery. Pagh and Cooper (1998) studied the effect of postponement strategies of producers on warehouse outbound processes, and our study evaluates the effect of postponing order cut-off times to obtain better responsiveness in terms of faster delivery speed. Such cut-off rules induce order peaks just before the cut-off time and cause imbalanced workloads. Huang et al. (2006) showed that these imbalances can lead to the 'self-contradiction of hands shortage and idleness' within the day. Such imbalances can be smoothed in several ways, for example, by modelling from historical data to reduce uncertainty (Gong and De Koster, 2011) and by balancing the workload (De Leeuw and Wiers, 2015). The labour intensive packing lanes of OEM warehouses are akin to factory workstations or job shops in manufacturing where productivity has been scrutinized via job-shop theory (Johnson, 1954). Our study pioneers the analysis of OEM warehouse outbound processes through job-scheduling methods using priority dispatching rules to smoothen warehouse flows and to optimize responsiveness.

Without prioritising, jobs are commonly processed on a first-come first-served (FCFS) basis. Jackson's rule (Jackson, 1955) orders jobs according to non-decreasing due dates, and this sequencing method is usually called 'earliest due date' (EDD). The shortest processing time (SPT) rule of Smith (1956) orders jobs according to non-decreasing processing times. Berry and Rao (1975) proposed two other rules, SLACK defined in terms of job slack (its due date minus its processing time) and critical ratio (CR) that corrects job slack for queuing delays. Kanet and Hayya (1982) presented an early application in manufacturing and compared priority methods based on due dates. Kiran and Smith (1984) studied dynamic job-shop scheduling by computer simulation, Lee et al. (1997) incorporated machine learning techniques, and Freiheit and Wei (2016) conducted a case study to investigate imbalance effects on flow-shop performance. Kemppainen (2005) presented an extensive comparison of various priority scheduling rules and their use in integrated order management.

The benefits of priority-based job scheduling can be evaluated in terms of operational and financial performance criteria. The choice which priority rule to employ involves a trade-off among multiple performance attributes of the outcomes, for example, handled volume, service level and operational cost (Chen et al., 2010). A popular method to assist this choice is data envelopment analysis (Hackman et al., 2001; De Koster and Balk, 2008). Treleven and Elvers (1985) assessed performance in terms of mean queuing times, mean earliness and percentage of late jobs. Ramasesh (1990) categorised performance in terms of idle machines, stalled promises, work-in-process inventories, and average value added in queue. Although contract terms often involve earliness and tardiness penalties (Baker and Scudder, 1990; Elsayed et al., 1993), T'kindt (2011) noted that most production cost models neglected just-in-time principles. Our study incorporates them 'en bloc' since warehouses face penalties both for tardiness because they have to meet carrier schedules and for earliness because pallets ataged for loading occupy costly storage space. Warehouse performance is evaluated in terms of a common cost criterion that integrates the objectives of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. The values of the cost parameters are case dependent, and a real-world case study for an EOM warehouse in consumer electronics specifies these parameters from operational data and investigates various cost scenarios depending on warehouse preferences across the performance dimensions. Other warehouses can incorporate this methodology in their own WMS for practical scheduling solutions derived from cost parameters and preferences that apply for their situation. In this way, our study supplements earlier studies like Cakici et al. (2012) that offered only theoretical solutions.

3. Simulation model and case study

The research question of central interest is how job priority scheduling can help OEM warehouses improving their responsiveness to meet current trends of postponed daily order cut-off times for next-day delivery. As customers adapt their ordering policy by spiking demand briefly before the cut-off time, warehouses are confronted with order peaks that have to be processed faster when response times become shorter. OEM warehouses usually dispatch retailer orders by truck on agreed pick-up times on the next working day. These pick-up times are spread across the day so that incoming orders have different due times that help job prioritization. As suggested by Van den Berg (2007), workload imbalances can be alleviated by distinguishing can-ship orders from must-ship orders and by shifting the former from busier to quieter hours. So, instead of processing orders on a FCFS basis, the workflow can be balanced by postponing less pressing jobs that have relatively late due times. Balancing the workload has several operational advantages, including reduced overtime and absenteeism reported in the empirical study of De Leeuw and Wiers (2015). The balancing effect of job priority management is illustrated graphically in Figure 1. By postponing part of the jobs stemming from demand peaks, the hourly workload becomes smoother with less peaks and troughs compared to FCFS scheduling.

<< *Insert Figure 1 about here.* >>

Ideally, the workload should be constant across the day as this greatly simplifies warehouse planning and operation. The incoming order arrival process is irregular so that this ideal situation cannot be achieved in reality. We investigate the performance of alternative scheduling strategies by a simulation study based on actual operational data of a case study warehouse. The methodology to improve order fulfilment responsiveness for postponed cut-off times consists of four steps:

(1) Build a simulation model of order fulfilment that includes the following operational aspects: arrival distributions, order peaks, due time distribution, service time distributions per operation, and a set of priority rules to schedule remaining jobs for each queue.

(2) Construct a cost objective function that incorporates penalties for earliness, tardiness, idleness, and work-in-process stock.

(3) Simulate the model under various cut-off scenarios and determine the costs resulting from each priority rule.

(4) Evaluate the relative performance of these priority rules for the various scenarios and identify which rule performs best under which circumstances.

For the case study warehouse, the simulation model of step (1) above has the following characteristics. The order fulfilment process consists of a tandem queue (Burke, 1956) with three service stages: picking, where a pallet or box is moved from storage to the packing lane; packing, where pallets are cubed according to customer requests; and staging, where pallets are moved from the packing lane to the staging zone. Figure 2 shows this tandem queuing process, where the three stages are linked without diversion and each stage consists of a set of servers with queues of unlimited capacity. The number of workers is fixed per service but varies between picking, packing and staging. Packing is the most labour intensive stage, with four workers per pallet. Packers perform re-palletizing and wrapping tasks to satisfy customer warehouse pallet size restrictions and they check that orders cubed as one pallet are complete before staging.

<< Insert Figure 2 about here. >>

As order arrival rates vary over the day, the arrival process at the picking stage is modelled as a non-homogeneous Poisson process with varying rates per hour of the day. Service times are modelled by simple exponential distributions with rates that differ for each of the three services of picking, packing and staging. The service rates for picking and packing depend on the order type, with a distinction between relatively simple single-item pallets (SIP) with faster rates and complex multi-item pallets (MIP) with slower rates. For given service and order type, the service rate is assumed to be constant per worker and per hour of the day. This assumption ignores ergonomic factors like fatigue, but the warehouse employs a refined measurement system for labour productivity per task per worker that indicates that this simplification is not unreasonable. All workers are directed independently via WMS instructions transmitted by hand-held terminals and they work per pallet without any knowledge of job priorities or shipment structures. The picking process is modelled as an M(t)/M/c queue with non-homogeneous Poisson arrivals, packing follows a G/M/c queuing model with arrivals determined by departures from upstream picking, and staging also follows a G/M/c queuing model with arrivals determined by upstream packing. The final phase of the order fulfilment process involves waiting, and the waiting time of pallets is defined as the length of time they stay at the staging zone after packing and before shipping.

Historical warehouse operational data are used to specify the simulation input parameters for hourly arrival rates (17, one for each hour of the working day from 6 am until 11 pm), service rates (6, one for SIP and one for MIP for picking, packing and staging), and the mix of SIP and MIP orders (with probability 0.77 for SIP and 0.23 for MIP). Due times are uniformly distributed over the 17 hours of the next working day, because the OEM warehouse planned its agreements with retailer warehouses to spread truck arrivals optimally over the day. Multiple orders from the same client are consolidated and have the same due time to reduce transport costs.

4. Priority rules and performance criteria

The literature review mentioned some well-known priority rules for job scheduling from flow-shop production theory, which will now be described in more detail. The simplest rule is first-come first-served (FCFS), where jobs that arrive earlier get higher priority. The so-called earliest due date (EDD) rule gives higher priority to jobs with earlier due time. Jackson (1955) proposed this priority rule and showed that it minimizes the maximum of job tardiness. In our OEM warehouse case study, the operational due time of dispatch by the carrier is already assigned upon arrival of the order owing to pre-arrangements with the retailers placing the orders. Smith (1956) proposed an alternative priority rule where jobs with shortest processing time (SPT) get highest priority to get minimal mean flow time, that is, minimal work-in-process inventories. This result is related to Little's law (Little, 1961), which states that in steady state the mean number of units in the system (L) equals the product of the mean arrival rate (λ) and the mean time the unit spent in the system (W), so that $L = \lambda \times W$. An opposite rule gives highest priority to jobs with longest processing time (LPT). In our case study, processing times are defined in terms of the expected total service time of all remaining operations, i.e., picking plus packing plus staging for the picking queue; packing plus staging for the packing queue; and staging for the staging queue.

EDD and SPT focus on tardiness performance, but earliness and post-completion costs are also relevant. Berry and Rao (1975) studied the slack time (SLACK) and critical ratio (CR) rules to improve inventory performance. For given time (t), the slack time (S_t) of a job with due time (D) is defined as the difference between remaining time ($D_t = D - t$) and (expected) remaining processing time (P_t) with correction factor ($c > 1$) to account for expected queuing and other time losses in the process, so that $S_t = D_t - c \times P_t$. SLACK gives higher priority to jobs with less slack time and constitutes a trade-off between EDD and LPT, as it assigns higher priority to jobs with earlier due times that take longer to process. Berry and Rao (1975) showed that this rule averts both inventory surpluses from early replenishment and inventory shortages from late supplier deliveries. Similar to EDD and SPT, the SLACK priority of a job is static in the sense that all priority parameters (due times and expected remaining processing times) are known upon arrival. CR is a dynamic rule and replaces the correcting factor (c) by the expected queuing times that apply during dynamic operation. This rule assigns highest priority to the job with the smallest value of remaining time until due time ($D_t = D - t$) divided by the sum of expected remaining processing time (P_t) and currently expected remaining queuing time (Q_t), that is, $(D - t)/(P_t + Q_t)$.

Here P_t depends on the stage of the job; for example, at the packing stage it involves the expected service times of packing and staging. Q_t depends not only on the stage of the job, but also on the queues it should still pass. These queues are dynamic and Q_t depends on the expected processing times of all unfinished jobs with higher priority. Putnam et al. (1971) reported that the CR rule reduces uncertainty by trimming lateness variance. In general, CR is expected to perform better than SLACK because it employs relevant extra dynamic information.

Table 1 provides a summary of the considered priority rules. EDD and SLACK reduce tardiness but may result in longer flow times than the alternatives. SPT and CR aim for short flow times but often lead or lag due dates with resulting weaker just-in-time and tardiness performance. Both SLACK and CR leverage processing times to account for other factors. CR provides dynamic corrections by means of "live" waiting times and is therefore expected to give shorter flow times than SLACK.

<< *Insert Table 1 about here.* >>

Next we consider performance criteria to evaluate OEM warehouse operations. The warehouse outcomes are evaluated in terms of a common cost criterion that integrates the four objectives of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. The weight of each objective is determined by the associated penalty for failing to reach it, and this cost structure will be case dependent. The cost criterion function for fulfilling a set of orders is given by

$$\text{Cost} = \sum_{i=1}^{n}(w_1 \times \alpha_i + w_2 \times \beta_i) + w_3 \times \gamma + w_4 \times \delta.$$

Here the symbols have the following meaning: 'i' denotes the order; 'n' is the total number of orders; 'α_i' is the earliness cost of job 'i' and involves space costs at the staging zone for awaiting pick-up; 'β_i' is the tardiness cost of the job and consists of demurrage costs for carriers from appointed pick-up time until actual dispatch time; 'γ' is the total idleness cost, the sum total of idle labour costs in the phases of picking, packing and staging; 'δ' is total work-in-process cost, the sum over all 'n' jobs of financial costs from work-in-process inventories during picking, packing, and staging; and 'w_i' (i=1,2,3,4) are selection weights that determine which objectives are incorporated (1 if yes and 0 if no), depending on the business environment.

The four objectives and expected performance of alternative priority rules are summarized in Table 2. Earliness penalties favour just-in-time strategies like SLACK by reducing staging buffer space, whereas CR and SPT exacerbate these penalties because of their shorter flow times. Tardiness penalties favour strategies like EDD that prevent lateness. Even though CR and SPT have shorter flow times, they tend to generate some very late jobs with large associated tardiness penalties. If favourable business relationships between warehouses and truckers allow rescheduling appointments without cost, then the tardiness penalty may be waived (w_2=0). Idleness and stock penalties, which are linked since curtailed stock-in-process requires less labour, are related to lean production principles (Krafcik, 1988). The law $L = \lambda \times W$ of Little (1961) implies that work-in-process inventories (L) and associated stock penalties are proportional to flow time (W), so that CR and SPT are expected to perform well in this respect. However, if handled products are relatively cheap so that inventory costs are negligible, then stock penalties could be discarded (w_4=0).

<< *Insert Table 2 about here.* >>

5. Simulation results

We investigate the cost performance of alternative job priority rules by a simulation study with parameters derived from a case study OEM retail distribution centre of a multinational consumer electronics manufacturer. Figure 3 summarizes the interactions of this distribution centre with its manufacturer, sales department, retail warehouses and shops, carriers, and labour provider. The order arrival process is determined by the sales department, and due times for order fulfilment are agreed with carriers.

<< *Insert Figure 3 about here.* >>

The main question of interest is how to improve responsiveness for postponed daily order cut-off times. Curve A in Figure 4 shows the historical hourly average order pattern for 2012-2014, with steep demand peak just before the order cut-off time that was fixed at 2 pm during that period. The simulation study considers postponed cut-off scenarios with cut-off time at 3 pm (B), 4 pm (C), or 5 pm (D). The corresponding demand patterns are simply extrapolated by shifting the base scenario (A) forwards in time while keeping the size of demand peaks and daily totals fixed.

<< *Insert Figure 4 about here.* >>

Table 3 summarizes the input parameters for the simulations derived from historical operational data of the case study warehouse. The sales order desk is open from 8 am until 6 pm and orders rarely arrive outside these hours, resulting in relatively small means and large standard deviations of arrivals for out-of-office hours. Order arrivals have 77% chance to be SIP and 23% to be MIP, and service rates for SIP are higher than those for MIP by factors 2.83 for picking and 1.34 for packing. Weekly idleness costs are obtained by multiplying the average non-utilisation ratio by the weekly sum of total labour costs of €21.93 per hour. Stock-carrying costs are derived from stock and space value and interest costs, with values per pallet per week of €10.14 for work-in-process stocks and €6.96 for storage in the staging zone. Time criticality of order fulfilment for this warehouse is shown by high demurrage costs of €75.00 per pallet per hour. Finally, for the correction factor c in the definition of slack ($S_t = D_t - c \times P_t$) we choose the same value (20) as in the pilot study of FCFS by Kanet and Hayya (1982) to correct machine processing time for queuing times. The average total processing time is 0.197 hours (1/12.94 + 1/9.40 + 1/73.13) for SIP and 0.376 hours (1/4.57 + 1/6.99 + 1/73.12) for MIP. This corresponds (for c = 20) to average fulfilment durations of 20×0.197 = 3.9 hours for SIP and 20×0.376 = 7.5 hours for MIP, which reasonably fits experiences in the case study warehouse

<< *Insert Table 3 about here.* >>

Every single simulation run corresponds to one week of warehouse operations with hourly order arrivals, order types, and order service times. A week consists of five days of 17 hours each (85 hours in total) with expected total arrival orders of around 3,200 pallets. One common set of 1,000 simulation runs is employed to study the outcomes of the five considered priority rules for each of the four cut-off scenarios (A-D). Each of these twenty scenarios is evaluated in terms of operational performance. The flow time of a job is the total time it spends in the shop, that is, the time elapsing between arrival and completion. Lateness is defined as the difference between completion time and due time, so that negative values correspond to timely completion. For smooth operation it is preferred to have not only small mean but also small variation of flow times and lateness, so that we consider both the mean and the standard deviation of these two characteristics across the set of jobs within a given simulation run, that is, a given week of warehouse operations. Tardiness occurs if lateness is positive, that is, if jobs are completed after the due time limit. Maximum tardiness is defined as the maximum value of (positive) lateness across all jobs within a given simulation run.

The operational outcomes of 1,000 simulation runs (weeks of order fulfilment) are summarized in Table 4 and Figure 5. Table 4 shows that postponed cut-off times lead, as expected, to shorter flow times, less lateness and more tardiness. FCFS does not perform well across all performance dimensions and has the worst tardiness outcomes, especially for tight cut-off scenarios. Of the five priority rules, CR performs by far the best in terms of flow time, whereas EDD and SLACK have excellent tardiness results as none of their jobs have positive lateness. Figure 5 shows some outlying tardiness results for CR, both in the benchmark cut-off scenario (A, 2 pm) and in the most ambitious scenario (D, 5 pm). SLACK and EDD perform roughly similar, but because SLACK amplifies the weight of processing times it has smallest lateness and longest flow times of all priority rules. Compared to these two methods, SPT has shorter flow times but more tardiness. The outcomes in Table 4 are in line with those in Table 1, because CR and SPT have shortest flow times, EDD and SLACK have lowest tardiness, and SLACK comes closest to just-in-time planning as it has highest lateness.

<< *Insert Table 4 and Figure 5 about here.* >>

Table 5 summarizes the financial outcomes of the simulation experiments. These outcomes consist of costs associated with earliness, tardiness, idleness, and stock costs. We consider an integrated cost function that includes all four cost components as well as two restricted versions. One version excludes stock costs, which is relevant for warehouses at urban locations with just-in-time planning that have relatively low stock value compared to high storage rental costs. Another version excludes tardiness costs for warehouses that handle high-priced goods with high storage rental costs and that have flexible pick-up agreements with carriers to skip tardiness penalties. EDD performs best if all components are included, SLACK is best if there are no stock costs, and CR is best if there are no tardiness costs. These rankings of priority rules do not depend on the cut-off scenario and get more pronounced for tighter scenarios. In scenario A (2 pm), the percentage of simulation runs for which EDD, SLACK and CR are optimal are respectively 46.5, 48.1, and 56.6, and for scenario D these percentages are respectively 93.7, 66.6, and 59.4. The outcomes illustrate that there is no priority rule that is universally best for all business situations, but each warehouse may find a suitable rule by selecting the performance objectives that apply for its specific situation.

<< *Insert Table 5 about here.* >>

As EDD and SLACK perform roughly similar, we provide a more detailed comparison of these two rules by means of paired t-tests (Welch, 1947) for operational and financial performance for the tightest cut-off scenario (D, 5 pm). The sample size of 1,000 runs far exceeds the usual rule-of-thumb threshold (30) so that we employ the conventional standard normal distribution to compute p-values. The results in Table 6 show significant differences between the two methods. In terms of operational performance, SLACK is more just-in-time and EDD has shorter flow time. From a financial perspective, SLACK requires less staging space but EDD has higher server utilization and less work-in-process stocks. The two rules do not show significant differences in tardiness and associated demurrage costs.

<< *Insert Table 6 about here.* >>

6. Some operational implications and conclusions

Enhanced competitiveness in retail markets asks for higher levels of responsiveness to satisfy consumer expectations. OEM warehouses, for example, can improve their order delivery speed by postponing order cut-off times for next-day delivery. To smoothen warehouse operations for efficient resource allocation, priority rules help in sequencing outstanding jobs at various stages of the warehouse process. The choice which rule to apply depends on the objectives and cost structure of the warehouse. The methodology proposed in this paper suggests careful examination of the business environment to identify relevant performance objectives and cost parameters. Historical operational warehouse data can be used to model the stochastic nature of the order arrival process and of the service and queuing times for the various stages of the outbound warehouse process.

In our analysis we distinguished performance along four dimensions by preventing earliness (staging costs), tardiness (demurrage costs), idleness (labour costs), and work-in-process inventories (stock costs). It depends on the business environment which of these dimensions are actually relevant. Preventing tardiness, for example, is imperative if delayed delivery spoils all product virtues, whereas it is less relevant if delays can be solved by penalty-free rescheduling of pick-up times. The latter situation often applies for OEM warehouses that deliver to retailer warehouses and shops. Our simulation results show that the critical ratio (CR) priority rule performs well in such situations. It offers shortest flow time with fewest work-in-process stock, which is valuable for businesses that handle expensive products with high labour costs.

The case study warehouse currently uses the earliest due date (EDD) strategy for sequencing its order fulfilment jobs. The simulation results based on the warehouse-specific cost parameters indicate potential benefits of the CR rule. Compared to the other priority rules, CR has the unique property that it incorporates the dynamic queuing status of jobs in determining their priority. The simulation study employs a rough estimate of queuing times based on expected processing times of jobs with higher priority. These estimates could be refined by studying actual workflow patterns and queuing data from the warehouse process and by forecasting queuing times using statistical and machine learning methods. The case study warehouse is interested in refining the job scheduling strategy in its WMS.

Summarizing the contributions of this paper, the current retail market leverages responsiveness of order fulfilment and forces higher levels of efficiency in distribution. From this perspective, job scheduling using flow-shop priority rules offers solutions for distribution centres facing cut-off time pressures. By prioritising each job, warehouses can efficiently maintain responsiveness without increasing labour to satisfy compressed order-fulfilment deadlines. The paper presents a simulation-based methodology for selecting priority rules by evaluating alternative rules in terms of composite cost objectives that can be tailored to warehouse-specific settings. Simulation results indicate good performance of the SLACK rule for just-in-time operations with high storage costs and of the CR rule for high-value product operations with flexible pick-up schedules.

Further research is needed to analyse the trade-off between potential revenue gains through better service with postponed cut-off times against increased costs due to tighter processing conditions. It is also of interest to study historical workflow patterns in more detail to refine CR-type priority rules by improving forecasts of remaining processing and queuing times.

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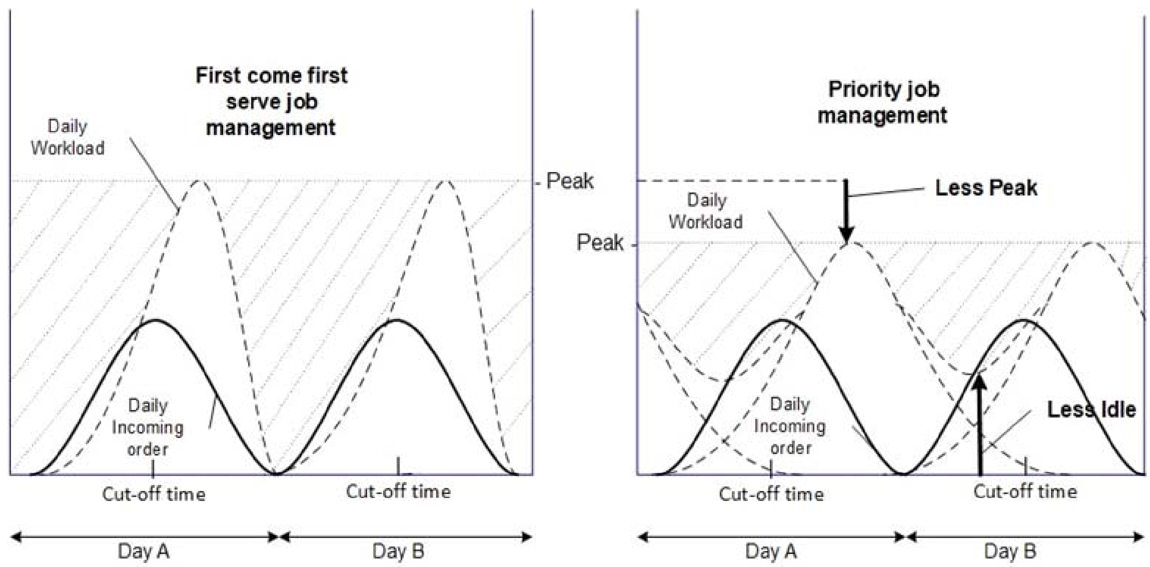

Figure 1. Daily incoming orders and two job management methods

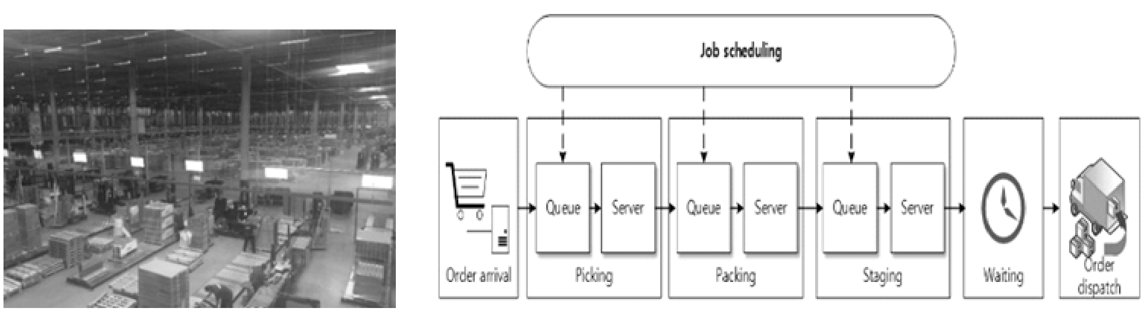

Figure 2. Actual warehouse process (left) and queuing model (right)

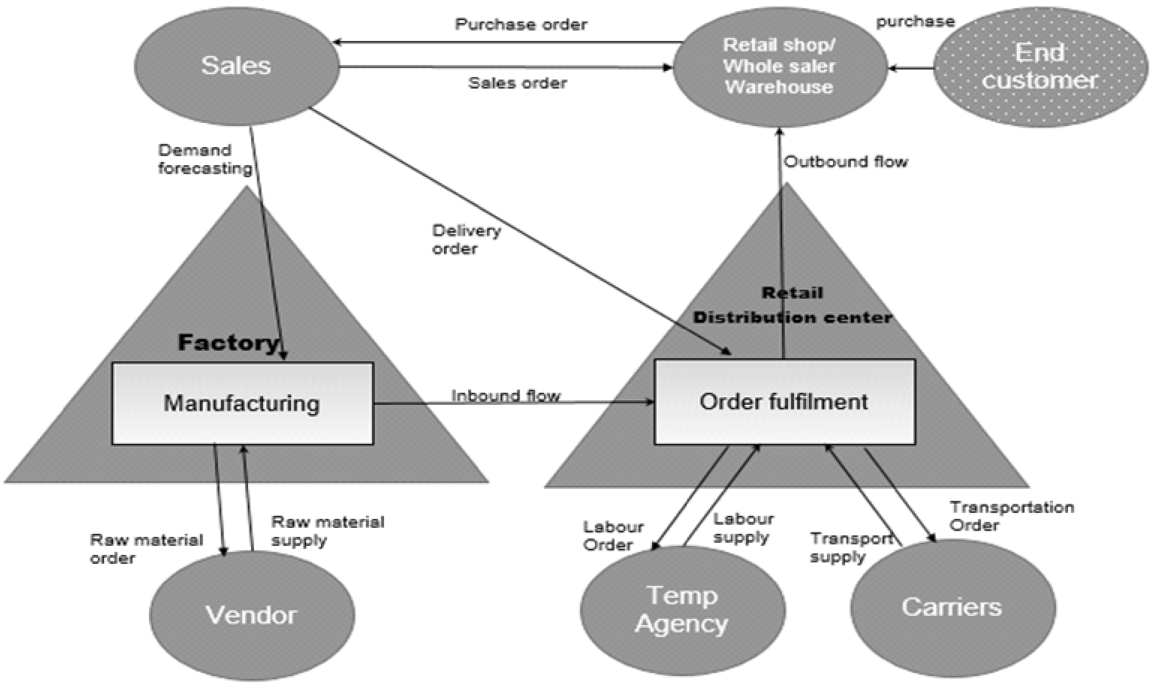

Figure 3. Retail distribution centre (OEM warehouse) and SCM partners

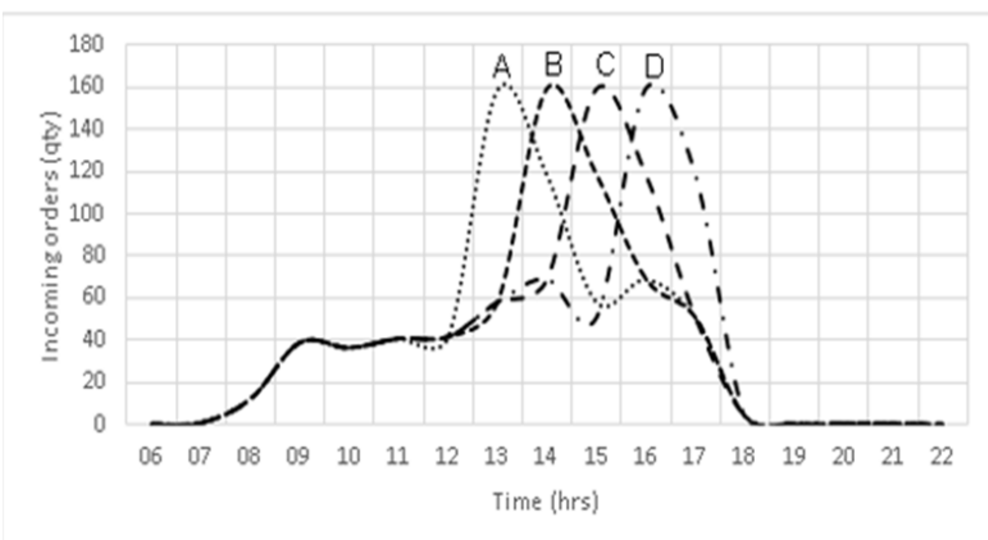

Figure 4. Average hourly incoming orders per for four cut-off scenarios (current is A)

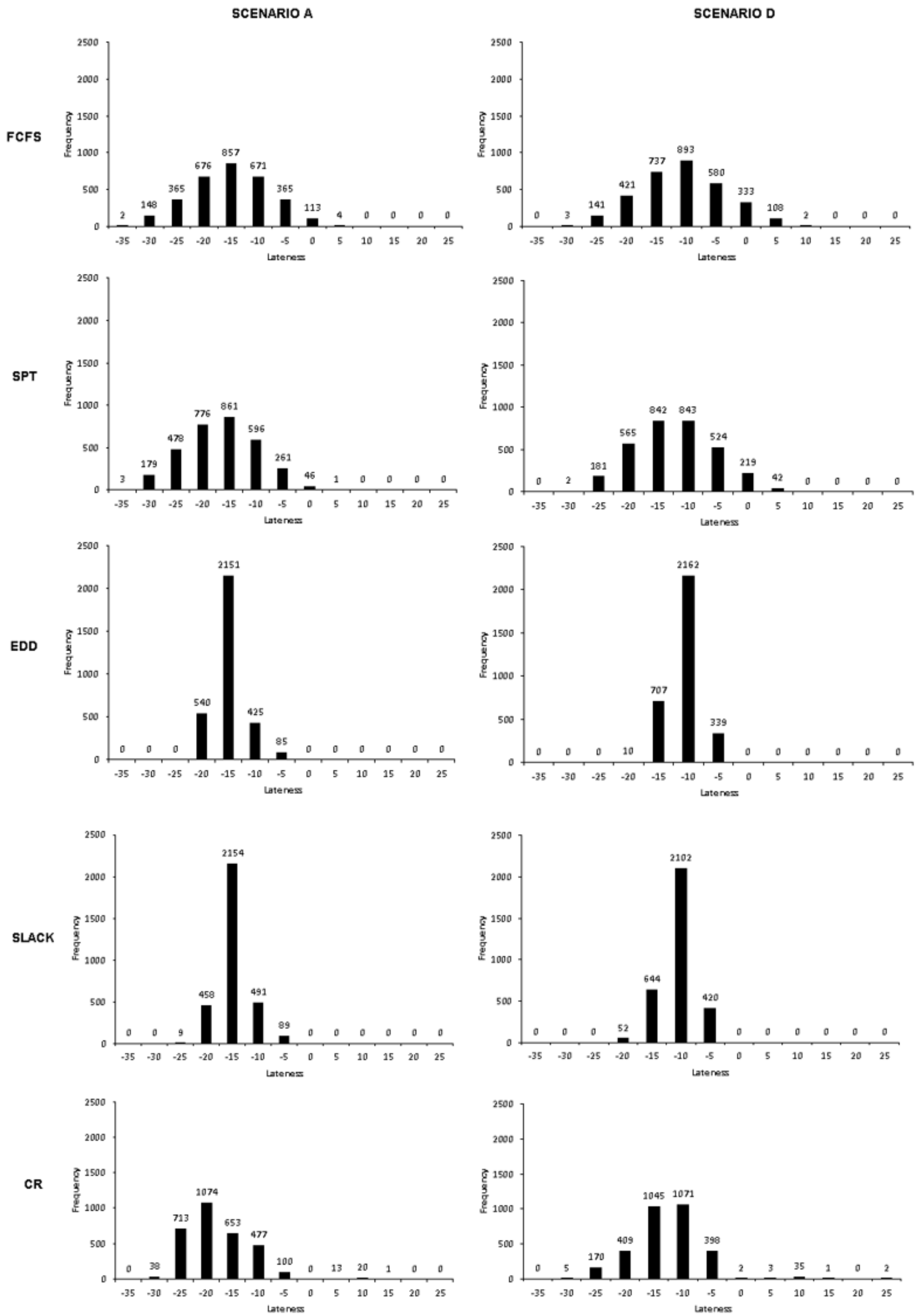

Figure 5. Histograms of simulated outcomes for lateness (0 on horizontal axis means -4.99 to 0.00)

Priority rule	Source	Performance objectives			
		Low tardiness	Short flow time	Just-in-time	Dynamic
First-come first-served (FCFS)	--	o	o	o	o
Earliest due date (EDD)	Jackson (1955)	+	o	o	o
Shortest processing time (SPT)	Smith (1956)	-	+	-	o
Minimum slack (SLACK)	Berry and Rao (1975)	+	-	+	o
Critial Ratio (CR)	Putnam et al. (1971)	-	+	-	+

Table notes
For each rule, + means advantage, - disadvantage, and o neutral performance for the objective.

Table 1. Performance of five priority rules for a set of four responsiveness goals

Penalty	Operations	Objective	Penalty Calculation			Priority rule	
			Cost Driver	Count	Unit cost	Advantage	Disadvantage
Earliness	Staging, appointment	Just-in-time	Staging stocks	Max	Storage cost (€ per pallet per week)	SLACK	CR / SPT
Tardiness	Appointment, dispatch	Early in time	Late hours	Sum	Demurrage cost (€ per pallet per hour)	EDD	CR / SPT
Idleness	Picking, packing, staging	Short flow time	Idle hours	Sum	Labour cost (€ per hour)	CR / SPT	SLACK
Stock	Picking, packing, staging	Short flow time	Work-in-process inventory	Average	Inventory value (€ per pallet per week)	CR / SPT	SLACK

Table notes
The sequence of operations consists of picking, packing, staging, appointment, and dispatch.

Table 2. Performance of various priority rules along four cost dimensions

Parameter		Unit	Specification	Value
Arrival rate		Pallets per hour	6-7 am	0.01 / 0.41
			7-8 am	0.85 / 20.86
			8-9 am	12.00 / 30.59
			9-10 am	38.82 / 54.65
			10-11 am	36.23 / 50.74
			11-12 am	40.70 / 57.53
			12-1 pm	41.46 / 58.94
			1-2 pm (cut-off)	158.84 / 116.53
			2-3 pm	118.00 / 142.31
			3-4 pm	57.88 / 71.95
			4-5 pm	68.68 / 86.70
			5-6 pm	50.64 / 84.02
			6-7 pm	3.94 / 21.62
			7-8 pm	0.34 / 5.17
			8-9 pm	0.53 / 7.94
			9-10 pm	0.43 / 6.90
			10-11 pm	0.01 / 0.33
Service rate	Picking	Pallets per hour per server	SIP	12.94
			MIP	4.57
	Packing	Pallets per hour per lane	SIP	9.40
			MIP	6.99
	Staging	Pallets per hour per server	SIP	73.13
			MIP	73.13
Penalty	Earliness	€ per pallet per week	storage cost	6.96
	Tardiness	€ per pallet per hour	demurrage cost	75.00
	Idleness	€ per hour	labour cost	21.93
	Stock	€ per pallet per week	work-in-process stock	10.14
	Queuing	Scalar value c	Slack = Dt - c×Pt	c = 20

Table notes

SIP and MIP denote respectively single-item pallets (77%) and multi-item pallets (23%).
Reported values are mean and standard deviation for arrival rates, mean for service rates, and financial penalty costs in terms of prime interest rates published by The Wall Street Journal for December 2016.

Table 3. Operational parameters for the case study warehouse (scenario A)

		Flow time				Lateness				Tardiness			
		Mean		Standard dev.		Mean		Standard dev.		Maximum		Fraction (%)	
Cut-off	Priority	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
2 pm	FCFS	8.7	2.3	2.9	0.2	-16.6	2.3	7.2	0.2	2.6	2.5	1.1	1.5
	SPT	7.3	2.1	5.0	0.7	-18.0	2.1	6.9	0.2	2.3	2.4	0.6	0.8
	EDD	8.7	2.3	6.9	1.0	-16.6	2.3	3.2	1.0	0.0	0.0	0.0	0.0
	SLACK	9.3	2.4	7.2	0.9	-16.0	2.4	3.3	0.9	0.0	0.0	0.0	0.0
	CR	4.8	0.5	6.9	2.2	-19.9	0.6	6.8	1.5	33.7	24.4	1.0	0.8
3 pm	FCFS	8.5	2.2	2.9	0.2	-14.9	2.2	7.2	0.3	3.9	2.8	2.2	2.5
	SPT	7.1	2.0	5.2	0.7	-16.4	2.0	6.9	0.2	3.6	2.7	1.1	1.4
	EDD	8.5	2.2	7.0	0.9	-15.0	2.2	3.0	1.1	0.0	0.0	0.0	0.0
	SLACK	9.2	2.3	7.3	0.9	-14.3	2.3	3.2	0.9	0.0	0.0	0.0	0.0
	CR	4.5	0.6	6.9	2.3	-18.3	0.6	6.7	1.5	35.2	23.2	1.1	0.8
4 pm	FCFS	8.4	2.3	2.8	0.2	-13.0	2.3	7.3	0.2	5.8	2.9	4.5	4.0
	SPT	6.9	2.1	5.1	0.6	-14.5	2.2	6.9	0.2	5.5	2.9	2.4	2.4
	EDD	8.4	2.3	7.0	0.9	-13.1	2.3	2.8	1.1	0.0	0.0	0.0	0.0
	SLACK	9.0	2.4	7.2	0.8	-12.4	2.4	3.0	0.9	0.0	0.0	0.0	0.0
	CR	4.3	0.6	6.8	2.4	-16.4	0.7	6.6	1.6	36.0	25.5	1.1	0.9
5 pm	FCFS	8.1	2.4	2.7	0.3	-11.7	2.4	7.2	0.2	7.0	3.1	6.8	5.2
	SPT	6.6	2.3	4.8	0.5	-13.2	2.3	6.9	0.2	6.7	3.1	3.9	3.3
	EDD	8.1	2.4	6.7	0.8	-11.7	2.4	2.7	1.1	0.0	0.0	0.0	0.0
	SLACK	8.8	2.5	7.0	0.7	-11.0	2.5	2.9	0.9	0.0	0.0	0.0	0.0
	CR	4.1	0.6	7.0	2.4	-15.0	0.7	6.5	1.6	37.7	25.2	1.2	0.8

Table notes

Underscored mean values are for the best performing priority rule per objective and per cut-off scenario.
Flow time, lateness and tardiness are measured in hours, and fraction of tardiness is measured as percentage.
The standard deviation colummns (std) show the variation of outcomes across the 1,000 simulation runs.

Table 4. Simulated performance of five priority methods

Objective		Earliness (α)		Tardiness (β)		Idleness (γ)				Stock (δ)	Cost specification								
Measurement		Max. stage		Truck penalty		Pick	Pack	Stage	Total	Average	All four (α + β + γ + δ)			No stock cost (α + β + γ)			No tardiness cost (α + γ + δ)		
Unit		Pallet		€		Utilization (%)				Pallet	€			€			€		
Cut-off	Priority	mean	std	mean	std						mean	std	best (%)	mean	std	best (%)	mean	std	best (%)
	FCFS	687	80	4,708	8,242	97.2	81.2	48.2	82.4	327.4	22,056	11,546	0.1	18,657	10,882	9.4	16,323	890	0.1
	SPT	712	82	2,350	4,220	97.2	81.7	48.6	82.8	274.9	18,687	6,396	46.6	15,831	5,807	2.7	15,766	794	43.3
2 pm	EDD	687	81	0.00	0.00	97.2	81.2	48.2	82.4	327.0	16,324	893	46.5	12,927	557	39.7	16,324	893	0.0
	SLACK	668	86	0.00	0.00	97.2	80.9	48.0	82.2	351.5	16,571	916	0.0	12,922	570	48.1	16,571	916	0.0
	CR	782	31	47,841	57,230	97.2	80.6	47.8	82.0	179.4	61,648	52,689	6.8	59,826	52,499	0.1	15,678	633	56.6
	FCFS	629	79	11,070	18,080	97.3	81.1	48.2	82.4	322.4	27,330	18,948	0.0	24,054	18,266	3.1	15,791	860	0.0
	SPT	657	67	5,614	9,769	97.3	81.7	48.7	82.9	268.1	21,056	10,360	26.2	18,334	9,758	3.3	15,203	811	48.1
3 pm	EDD	629	80	0.00	0.00	97.3	81.1	48.2	82.4	321.6	15,780	857	69.4	12,515	581	40.4	15,780	857	0.0
	SLACK	607	87	0.00	0.00	97.3	80.7	47.9	82.1	346.2	16,024	875	0.0	12,508	596	53.2	16,024	875	0.0
	CR	726	29	50,023	62,785	97.3	80.5	47.8	81.9	170.9	62,125	55,679	4.4	60,394	55,495	0.0	15,121	600	51.9
	FCFS	561	82	26,973	33,274	97.2	81.2	48.3	82.4	316.6	45,424	35,018	0.0	42,088	34,249	0.4	15,366	925	0.0
	SPT	607	52	14,222	18,379	97.2	82.1	49.0	83.2	260.9	30,480	19,675	6.8	27,718	18,973	0.4	14,799	925	42.9
4 pm	EDD	561	83	0.00	0.00	97.2	81.2	48.3	82.5	315.9	15,347	928	87.3	12,018	601	35.0	15,347	928	0.0
	SLACK	535	89	0.01	0.25	97.2	80.8	48.0	82.1	340.9	15,583	949	0.1	11,994	610	64.2	15,583	949	0.0
	CR	657	31	53,694	70,056	97.2	80.7	47.9	82.1	163.9	64,066	66,456	5.8	62,415	66,254	0.0	14,610	644	57.1
	FCFS	509	85	45,756	48,295	97.2	81.2	48.3	82.4	307.0	63,757	48,231	0.0	60,559	47,444	0.0	14,865	926	0.0
	SPT	572	55	24,732	27,716	97.2	82.2	49.1	83.3	250.1	40,158	27,733	0.8	37,544	27,016	0.0	14,335	951	40.6
5 pm	EDD	508	87	0.00	0.00	97.2	81.2	48.3	82.4	305.5	14,848	912	93.7	11,661	563	32.9	14,848	912	0.0
	SLACK	480	89	0.06	1.27	97.2	80.8	47.9	82.1	330.8	15,164	1,709	0.1	11,715	1,393	66.6	15,080	941	0.0
	CR	604	33	60,877	68,854	97.2	80.8	47.9	82.1	155.8	75,991	65,710	5.4	74,406	65,517	0.5	14,116	644	59.4

Table notes

Idleness costs are for operation with 25 workers: 4 pickers, 5 packing lanes with in total 20 packers, and 1 stager.

Best (%) shows the percentage of all 1,000 simulation runs where this priority rule has lowest cost across the five considered rules.

The standard deviation columms (std) show the variation of outcomes across the 1,000 simulation runs.

Table 5. Simulation outcomes of five priority rules for three customized performance criteria

			Mean Value			Significance		
Evaluation	Objective	Unit	EDD	SLACK	GAP	t-statistic	p-value	Differ
Operational	Flow time	Hour	8.1	8.8	-0.7	-6.050	0.000	Yes
	Lateness	Hour	-11.7	-11.0	-0.7	-6.034	0.000	Yes
	Tardiness	%	0.0000	0.0002	-0.0002	-1.415	0.157	No
Financial	Max pallet staging (α)	Pallet	508	480	28	6.992	0.000	Yes
	Truck penalty (β)	€ / week	0.000	0.057	-0.057	1.416	0.157	No
	Server utilization (γ)	%	82.4	82.1	0.3	5.710	0.000	Yes
	Stock in progress (δ)	Pallet	306	331	-25	-6.050	0.000	Yes

Table notes

GAP is the difference between EDD and SLACK.

The p-value is based on the two-tailed t-distribution.

The column 'Differ' shows whether EDD and SLACK differ significantly (at 5% level).

Table 6. Welch t-test results for differences between EDD and SLACK priority rules (cut-off scenario 5 pm)