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Improving well-being and efficiency in order picking ⋆

Marco Giacomelli [*] **Arpan Rijal** [**] **Francesco Pilati** [*]
Kees Jan Roodbergen [**]

[*] *Deparment of Industrial Engineering, University of Trento, Trento 38122, Italy (e-mail: marco.giacomelli-2@unitn.it; francesco.pilati@unitn.it).*
[**] *Faculty of Economics and Business, University of Groningen, Groningen 9747 AE, The Netherlands (e-mail: a.rijial@rug.nl; k.j.roodbergen@rug.nl)*

Abstract: For processes that rely largely on manual activities, such as order picking, human factors need to be considered for aligning decision-making with actual system performance. This paper proposes a joint order picking batching and sequencing problem formulation with worker fatigue modeling. The fatigue level induces a decrease in performance, thus making the picking time for any batch dependent on prior sequence position decisions. Moreover, overly fatigued operators may necessitate rests. This optimization problem is solved with Adaptive Large Neighborhood Search meta-heuristic for a realistic warehousing scenario. It is shown how considering the fatigue effect can improve both efficiency and worker well-being.

Keywords: Order Picking, Fatigue, Meta-heuristics, Sustainable operations

1. INTRODUCTION

Responding to customer demands in any supply chain network requires product retrieval from storage systems. Order picking operations enable this goal and are largely based on manual activities (De Koster et al., 2007). Due to this characteristic, and in accordance with the Industry 5.0 paradigm (European Commission et al., 2021), it is imperative to include human factors when dealing with order picking. Grosse et al. (2017) state how such aspects, like fatigue and injury risk, are affected by order picking decision problems. In this regard, De Lombaert et al. (2023) emphasize the importance of a human-centered approach in the automation and digitization of warehouse processes, especially with the transition from Industry 4.0 to Industry 5.0.

Order picking, especially when orders are small, can benefit from batching, defined as collection of multiple customer orders within the same picking tour (De Koster et al., 2007). Pardo et al. (2024) define the decision problems directly related to batch formation, namely sequencing for collection of the determined batches, and routing between each order-line location for each tour. Additionally, they state how batch assignment needs to be tackled whenever multiple pickers are present. The shift in perspective towards more socially-sustainable warehouse systems is particularly relevant in the context of batching and sequencing, where operational decisions can have a direct impact on worker fatigue and productivity.

While the major focus in the order picking literature that considers human factors is related to tactical decisions, like storage assignment, according to the analysis of Grosse et al. (2017) the same does not seem to be true for operational problems such as batching or routing. A key human factor relevant in these scenarios is worker fatigue, which is a multi-faceted aspect that can have an effect on productivity (Jaber et al., 2013). According to Ferjani et al. (2017), fatigue is one of the key factors affecting worker performance, leading to degradating processing times of tasks for increasing fatigue levels. Human characteristics such as fatigue in fact affect the time needed to execute manual tasks, which can be modeled as a function of fatigue for operational optimization problems (Prunet et al., 2024). These operational issues, though often overlooked, significantly affect the efficiency and well-being of workers, underlining the need for a more comprehensive approach to human-centric optimization.

Order picking is characterized by the execution of different types of tasks. Xu and Hall (2021) analyzed the literature and identified fatigue models for such scenarios. Within the analyzed works, Zhao et al. (2019) appears to be the only contribution considering performance effects of fatigue for order picking. In particular, they tackle the operational problem of single-tour optimization as a scheduling problem. They model the effect of fatigue on a task as dependent on its position in the tour sequence and on the worker fatigue rate. However, this approach contrasts the fact that in order picking tasks can be largely diverse, hence possibly contributing in different ways to worker fatigue and performance degradation. For example, Glock et al. (2019) link different ergonomics effects to the picking of items depending on height and position for products stored on pallets by using biomechanical modeling. Another primary component of order picking work is

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travel. In this regard, De Lombaert et al. (2024) do not find any relation between walked distance of order pickers and their physical well-being.

To promote better working conditions and improving performance of order picking, this paper presents a human-centric optimization framework for the batching and sequencing problem. The aim is to prevent worker strain by implementing a quantitative measure of fatigue that depends on the picking tasks to be executed. Additionally, it is considered how batch execution performance depends on such fatigue measure, effectively linking the picking time of any task to the decisions of both previous and current batches. This highlights the importance of considering time factors other than the travel one, historically the major focus in order picking optimization problems. Moreover, in order to reduce worker strain, a rest approach is proposed and tested. Similarly to Martina Calzavara and Visentin (2019), exponential fatigue build-up and recovery during rest are considered, with a rest approach that integrates with the proposed granular estimation of fatigue and aims both at containing fatigue levels and mitigating the negative effects on performance.

The remainder of this paper is organized as follows. Section 2 presents the formulation for the picker-to-parts batching and assignment problem and the related fatigue and rests models. Section 3 overviews the employed optimization method, followed by Section 4, aimed at presenting relevant numerical results for a class-based warehousing scenario, obtained with meta-heuristic optimization. Finally, Section 5 summarizes the main findings as well as implications for future research.

2. JOINT BATCH AND SEQUENCING PROBLEM

The tackled optimization problem deals with the batch formation and sequencing of a set of orders for an order picker. It is assumed that all orders are known in advance, and that each order can be constituted of multiple items that cannot be separated in different batches. Picking time for each item is non-constant as it depends both on the orders constituting a batch, and its sequence within the set of batches due to the build-up of the worker fatigue level.

The goal is to minimize total picking time of all orders for the single-picker problem, considering that each order needs to be completed in one of the resulting batches. The time to execute a batch depends not only on the orders constituting a batch, but also on the decisions related at batches executed at previous sequence positions. More specifically, the time to complete the pick of order line is a function of worker fatigue level at the start of the task and it includes both travel time from previous pick location and pick execution time at the current location. By integrating this detailed relation between operational decisions and human factors, a punctual estimation of fatigue can be obtained for each task. The estimation of picking time is itself dependent on the fatigue metric and is detailed in Section 2.1.

Each batch has a maximum capacity defined by the total number of order lines of the assigned orders and is executed within a single picking tour that starts and ends at the depot. Considering a dedicated storage allocation policy, the sequence of execution of tasks within a batch is given by routing decisions, considered outside of the scope for the proposed optimization problem. Each order is constituted by one or more retrieval tasks, and can be assigned only to a single batch for order fulfillment.

2.1 Fatigue modeling and effect on performance

As previously introduced, the fatigue level of the worker affects the performance of executing a picking action. The fatigue model is presented and its relation to system characteristics and picking performance is detailed. For any item i assigned to batch k, the execution time θ_{ik} for the lifting and lowering portion of the pick depends on the fatigue level of the worker at the start of the task:

$$\theta_{ik} = \hat{\theta}_i(1 + \lambda \ln(1 + F_{s_{ik}-1})), \qquad (1)$$

where $\hat{\theta}_i$ is the theoretical picking time for item i. The degradating performance due to fatigue is assumed as logarithmic (Ferjani et al., 2017), scaled by the factor λ, where $F_{s_{ik}}$ indicates the fatigue level, between 0 and 1, of the worker at the end of task i sequenced in position s_{ik} within batch k. Both the orders assigned to a batch and the sequencing of the batch with respect to the others affects how fatigue builds-up, and thus influences the performance of the execution of each task. In addition, the completion of the pick of each item i, including the return to the depot, takes into account the travel time d_{li} between the locations of the task sequenced in $s_{li} = s_{ik} - 1$ and s_{ik}, where l is the task executed before i in the same picking tour, starting from the depot.

The fatigue at the end a task is a unitary measure modeled assuming exponential fatigue build-up in task time (Jaber et al., 2013). Moreover, as in Ferjani et al. (2017), the fractional increase in fatigue is a function of fatigue level at the start of the task (Eq. 2), or equivalently at the end of the previous task assuming that travel does not influence the fatigue level.

$$F_{s_{ik}} = F_{s_{ik}-1} + (1 - e^{-p_i \theta_{ik}})(1 - F_{s_{ik}-1}) \qquad (2)$$

The penibility rate $p_i > 0$ defines how quickly fatigue of the worker can increase for the pick of item i, therefore differentiating the effect on fatigue of different tasks. For example, heavier items or items stored in higher shelf levels can be linked to bigger fractional increases in fatigue level. In each picking tour, the order picker will perform several picking tasks with different penibility values. For constant starting fatigue level, higher penibility values are linked to higher rates of fatigue accumulation with task time.

2.2 Rest modelling

The fatigue level is restricted by a threshold value F_{max}, meaning that, to avoid excessive strain on the worker, dedicated rest is needed to reduce residual fatigue caused by a previous task. For any picking task i sequenced in position s_{ik} in batch k, a rest of duration $\tau_{s_{ik}}$ is issued right before pick execution with the aim to allow for recovery after having reached the location of the item to be picked.

The duration of the rest (Eq. 3) is given by the time it takes to achieve a predetermined level R_L of residual fatigue. In other words, if $F_{s_{ik}} > F_{max}$, then the worker has to rest

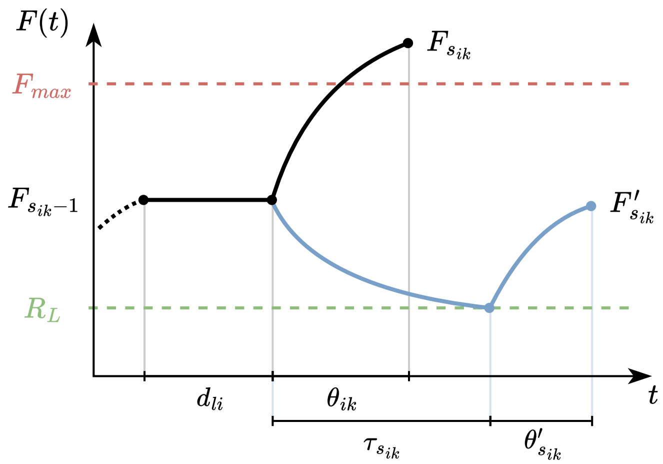

Fig. 1. Visualization of the time components for completion of task i sequenced in position s_{ik} in the rest scenario (blue) and the standard scenario (black).

for lowering the value of fatigue level at the start of the task ($\equiv F_{s_{ik}-1}$) to R_L, as shown in Figure 1. If no rest is executed, no recovery is observed and fatigue will surpass the threshold, while also resulting in larger processing time for task in position s_{ik}.

$$\tau_{s_{ik}} = \mu^{-1} \ln(F_{s_{ik}-1}/R_L) \tag{3}$$

Equation (3) assumes exponential decrease in fatigue level with time (Jaber et al., 2013), where μ indicates the rest rate.

The resulting fatigue level at the end of a task that necessitates rest is given by:

$$F'_{s_{ik}} = R_L + (1 - e^{-p_i\theta'_{ik}})(1 - R_L) \tag{4}$$

with adjusted θ'_{ik} computed with starting fatigue level R_L. Moreover, the task time t_{ik} will include rest time $\tau_{s_{ik}}$, hence impacting total completion time for batch k. On the other hand, due to the monotonicity of the task time with respect to the fatigue level, the execution of the pick task will be shorter.

3. OPTIMIZATION METHOD

The optimization problem for joined batch formation and sequencing, paired with fatigue and rest modeling is tackled with Adaptive Large Neighborhood Search (ALNS) meta-heuristic with simulated annealing acceptance criterion (Ropke and Pisinger, 2006). At each algorithm iteration, the solution neighborhood is explored by applying one removal operator followed by an insertion one. Each of these heuristic steps happens with a choice of a pair of operators following a roulette-wheel selection based on operators weights. At each iteration, scores are assigned to the used operator pair based on if the new solution is a global best, if it is better than the current solution, or if it is worse. The simulated annealing criterion permits the exploration of worse solutions depending on the current temperature, which decreases at a constant rate at each iteration. After a fixed number of iterations, also called segment, operator weights are updated based on the scores. This adaptive weight adjustment mechanism allows for favouring the heuristics that perform better for the studied problem instance. The stopping criterion is the number of iterations.

Table 1. Parameters for triangular distributions used for picking time and penibility of each item.

Class	Task time $\hat{\theta}_i$ [s]	Penibility p_i
A	$T\,[8, 16]$	$T\,[.04, .06]$
B	$T\,[4, 10]$	$T\,[.01, .05]$
C	$T\,[2, 6]$	$T\,[0, .02]$

The employed removal operators are either random or worst order removal from any batch, where the worst order is identified by the biggest change its removal brings in the objective function. Insertion can happen as random or greedy. Additionally, a heuristic neighborhood step can be performed with one of the swapping operators. More specifically, swapping of orders or entire batches are considered.

The sequence of picks within each batch is the result of the S-shape routing heuristic (Roodbergen and Koster, 2001), which defines also the travel time between picks, assuming constant travel speed and no effect of fatigue on travel.

4. NUMERICAL EXPERIMENTS

In order to generate insights and realistic results, a simulated warehouse scenario is generated and used for numerical experiments. A two-block warehouse with $N = 200$ product locations is considered, assuming dedicated storage assignment. Each location has a size of 2×2 meters, and all the aisles are 2 meter wide. Based on distance from the depot, located in at the beginning of the front-aisle, To reflect common practitioner storage allocation decisions, the warehouse operates under ABC classes, with 10% of the locations dedicated to A-class items, 20% to B-class, and the remainder to C-class, as depicted in Figure 2.

Demand instances are generated based on the roulette wheel method with ABC class probabilities of 80%, 15%, and 5 % respectively. Each instance has between 100 and 200 orders, each with 1 to 5 items. The theoretical time for picking each item i is triangularly distributed and depends on product class, while task time and penibility for depot is assumed as null. Table 1 reports the used time distributions for each class, where T $[a, b]$ indicates a triangular distribution with lower limit a and upper limit b, and mode $(a + b)/2$. Different item categories may require varying standard picking times because of product dimensions or other handling requirements. It is assumed that A-class items require more time for picking with respect to other classes, and B-class task times are higher than C-class. Similarly, task penibility indices are generated following a triangular distribution for each class, where A-class items are related to higher penibility values. On average, for null worker fatigue level, the fractional increase in fatigue is 45.1% (18.9%) for the pick of an A-class (B-class) item.

4.1 Results and discussion

The ALNS metaheuristic is tested on two classes of problems. The first class considers the proposed rest approach, while the second does not consider rest and allows for fatigue build-up regardless of the threshold F_{max}. More specifically, each problem class optimization is tackled firstly by considering the fatigue effect on performance. Then, the degradating effect of fatigue on task time is ignored (i.e, $\lambda = 0$). For this scenario, the optimization results are evaluated considering the link between performance and fatigue to depict the scenario where worker fatigue is ignored during decision-making.

Batch capacity is of assumed of 15 items, and the order picker has a maximum fatigue level of 90%, with a related value of recovery level R_L of 40%. The scale factor for the effect of fatigue on picking task duration is $\lambda = 2$. This scaling factor means that if the worker fatigue level approaches its maximum, then the picking performance decreases to 41% compared to the theoretical one. Moreover, the recovery speed is assumed as moderate ($\mu = 0.02$). The ALNS runs are constituted by 50,000 total iterations with 100 segments, with the parameters reported in Table 2.

Tests are related to 10 randomly-generated demand instances. Results highlight how actively considering fatigue effect on performance allows to achieve better total picking times in both the considered problem classes. Table 3 shows, for each instance, the total picking time T and average worker fatigue level $\bar{F}$ considering the rest scenario (r) and no-rest one (n) for the proposed batching and fatigue formulation. Additionally, T' and $\bar{F}'$ refer to total picking time and average fatigue level for the optimization results of the batching formulation that ignores fatigue, then evaluated considering degradating performance. Specifically, these results replicate standard planning decisions that do not consider human factors and their effect on real system performance, considering how workers experience fatigue due to manual work depending on batching solutions.

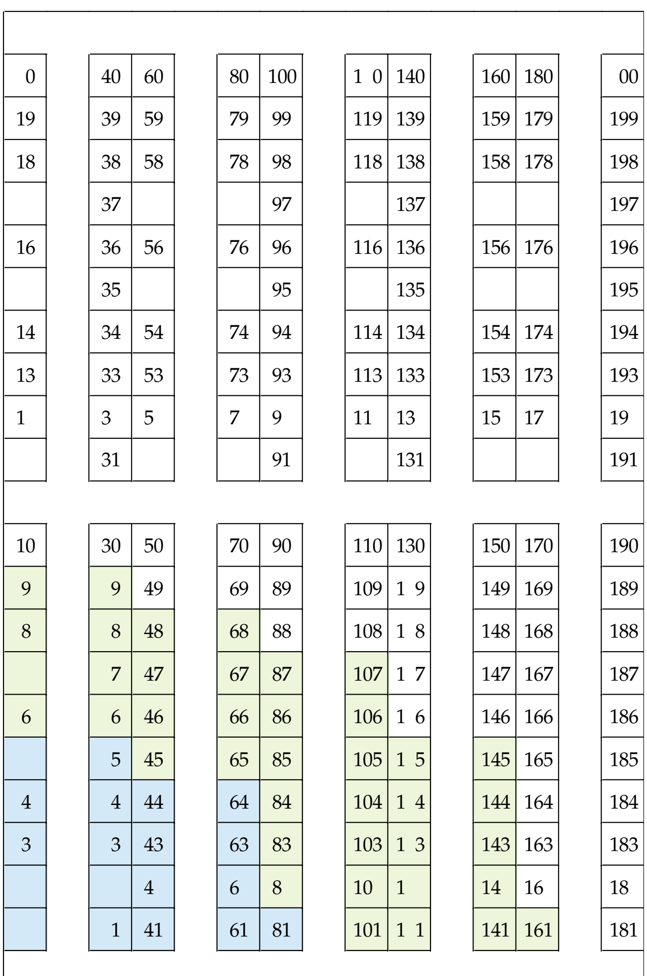

Fig. 2. Warehouse layout. Locations for class A (blue), B (green), and C (white) items are reported.

Table 2. ALNS paramters (Ropke and Pisinger, 2006). Scores refer to new global best, new better, and new worse solution respectively.

Parameter	Value
Scores	{33, 9, 13}
Reaction factor	0.1
Colling rate	0.99975
Worsening factor	0.05

When the rest approach is considered, neglecting fatigue results 2.3% worse performance on average while increasing the mean fatigue level of more than 6%. This difference in the performance values between considering and ignoring fatigue is the result of different batching and sequencing choices. A lesser but still relevant effect can be observed for the scenario that does not include dedicated rest time, where 0.7% of increased performance can be obtained by shifting to the fatigue-dependent time formulation whilst improving the mean fatigue level of around 3%.

The performance differences between the two analyzed classes is prevalent. Within the test instances, the rest times due to the fatigue constraint have a great effect on total picking time. Maintaining better working conditions by limiting the human factor of fatigue to fulfill the same customer orders can cost between 21 and 25% of total time performance. On the other hand, dedicating time for rest can improve average fatigue level up to more than 43%.

Given the impact of the rest approach, further analyses focus on the effect of rest-related parameters on total

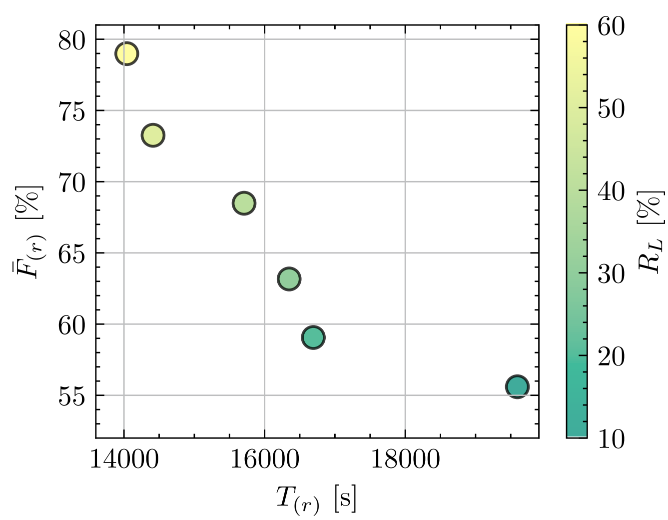

Fig. 3. Resulting total picking time and average fatigue level of the fatigue-rest model for varying recovery leveles for Instance #0.

Table 3. Results and characteristics for the tested demand instances.

			Rest approach				*No fatigue threshold*			
Instance	# orders	# lines	$T_{(r)}$ [s]	$\bar{F}_{(r)}$ [%]	$T'_{(r)}$ [s]	$\bar{F}'_{(r)}$ [%]	$T_{(n)}$ [s]	$\bar{F}_{(n)}$ [%]	$T'_{(n)}$ [s]	$\bar{F}'_{(n)}$ [%]
0	184	564	15,707	68.5	16,119	74.6	12,045	98.0	12,208	99.5
1	107	326	9,052	70.1	9,238	73.8	6,941	94.7	7,010	99.3
2	113	319	8,852	69.4	9,121	73.6	6,676	94.8	6,725	99.3
3	111	294	8,154	70.4	8,339	74.6	6,229	95.8	6,284	99.2
4	142	427	11,745	69.3	11,949	72.4	9,039	97.2	9,153	99.5
5	109	337	9,186	69.0	9,370	73.6	7,150	96.4	7,157	99.5
6	100	288	7,335	68.9	7,518	73.7	5,800	95.4	5,893	99.2
7	173	534	14,107	69.7	14,449	73.8	10,942	96.9	11,009	99.7
8	167	485	13,173	68.4	13,378	73.6	10,199	98.0	10,146	99.1
9	178	523	13,761	68.5	14,142	72.5	10,817	97.1	10,855	99.7

picking time. Firstly, the effect of the rest rate is investigated by assuming $\mu = 0.05$, considered as fast recovery according to Jaber et al. (2013). Similarly, slow rest rate is also investigated ($\mu = 0.01$). The average total picking time is 2.8% and 72.7% larger for fast and slow recovery respectively with respect to ignoring the fatigue threshold. These results for average total picking time deviations from the no-rest scenario underline the impact of rest time on the objective function, since higher rest rates allow to recover to the desired level faster.

Another parameter that directly affects rest times is the recovery level R_L. The effect of the residual fatigue reached after rest whenever the fatigue threshold is surpassed is investigated for the first demand instance. More specifically, Figure 3 shows the result of varying values of residual fatigue and how this has an impact on both total picking time and on the average fatigue level of the worker. With increasing R_L values, the average fatigue also increases, while the objective function value decreases. For the studied fatigue and rest functions, this suggests that additional time for recovery of the worker allows for better working conditions at the cost of an increase in total picking execution time.

A similar trend is also true for varying maximum fatigue threshold levels. As shown in Figure 4 for a recovery level of 40%, for increasing F_{max} the average worker fatigue level increases, while the total picking time of all orders decreases. These results are in line with the comparison between the rest and no-rest problems, where there is an inverse relation between the time and human factor perspectives.

5. CONCLUSION

This paper presented an original optimization model that captures the human factor of fatigue within order picking optimization, highlighting how benefits can be obtained by assessing its degradating effect on performance within the optimization model. In particular, better working conditions can be achieved considering that fatigue level is lowered compared to the scenario where fatigue is ignored in decision-making. Further improvements in fatigue can be achieved by implementing rests, even though this aspects can impact performance depending on the amount of resting time allowed.

By supporting operational planning decisions for order picking with explicit models that consider human factors, the interaction between time performance and working conditions can be analyzed. The current study emphasizes the importance of considering fatigue in order picking optimization models, enabling the consideration of trade-offs when designing work schedules and rest policies to optimize both worker well-being and operational efficiency. Balancing the need for adequate rest with the demands of productivity can lead to more sustainable and effective work environments.

Future research may focus on extending the relation of fatigue to performance also considering the heterogeneous workers. Sources of heterogeneity can strive from individual physical fitness, cognitive abilities, and work experience. Given the explicit nature of the proposed model, such differences can be integrated with minimal efforts for multi-picker scenarios. Further studies could also explore the effects of fatigue on work quality, and examining psychological factors like boredom and learning. Moreover, results suggest that investigation on different rest approaches should be explored due to its important effect on fatigue and performance. Another key aspect is

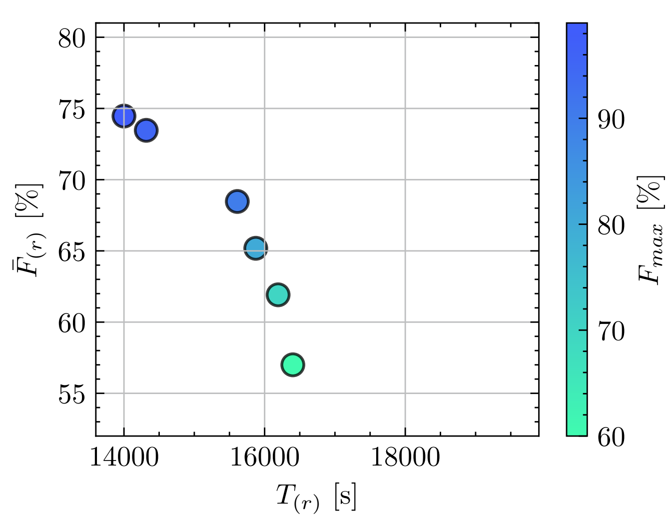

Fig. 4. Resulting total picking time and average fatigue level of the fatigue-rest model for varying fatigue thresholds for Instance #0.

the identification of the parameters related to penibility of task execution, as they may depend on worker other than product characteristics. Other rest policies could be investigated as well, for example moving towards less efficient but more applicable rest pooling between batches. By understanding the interplay between human factors and operational decisions, we can develop more effective strategies for order picking that benefit both workers and the supply chains as a whole.

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REFERENCES

De Koster, R., Le-Duc, T., and Roodbergen, K.J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, 182, 481–501. doi:10.1016/j.ejor.2006.07.009.

De Lombaert, T., Braekers, K., De Koster, R., and Ramaekers, K. (2023). In pursuit of humanised order picking planning: methodological review, literature classification and input from practice. *International Journal of Production Research*, 61(10), 3300–3330. doi: 10.1080/00207543.2022.2079437.

De Lombaert, T., Braekers, K., De Koster, R., and Ramaekers, K. (2024). What makes order picking so physically demanding? – ergonomic evidence from a large-scale lab experiment using subjective metrics. *IFAC-PapersOnLine*, 58(19), 181–186. doi: https://doi.org/10.1016/j.ifacol.2024.09.139. 18th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2024.

European Commission, Directorate-General for Research and Innovation, Breque, M., De Nul, L., and Petridis, A. (2021). *Industry 5.0 – Towards a sustainable, human-centric and resilient European industry*. Publications Office of the European Union. doi:doi/10.2777/308407.

Ferjani, A., Ammar, A., Pierreval, H., and Elkosantini, S. (2017). A simulation-optimization based heuristic for the online assignment of multi-skilled workers subjected to fatigue in manufacturing systems. *Computers and Industrial Engineering*, 112, 663–674. doi: 10.1016/j.cie.2017.02.008.

Glock, C.H., Grosse, E.H., Abedinnia, H., and Emde, S. (2019). An integrated model to improve ergonomic and economic performance in order picking by rotating pallets. *European Journal of Operational Research*, 273, 516–534. doi:10.1016/j.ejor.2018.08.015.

Grosse, E.H., Glock, C.H., and Neumann, W.P. (2017). Human factors in order picking: a content analysis of the literature. *International Journal of Production Research*, 55, 1260–1276. doi: 10.1080/00207543.2016.1186296.

Jaber, M.Y., Givi, Z.S., and Neumann, W.P. (2013). Incorporating human fatigue and recovery into the learning-forgetting process. *Applied Mathematical Modelling*, 37, 7287–7299. doi:10.1016/j.apm.2013.02.028.

Martina Calzavara, Alessandro Persona, F.S. and Visentin, V. (2019). A model for rest allowance estimation to improve tasks assignment to operators. *International Journal of Production Research*, 57(3), 948–962. doi: 10.1080/00207543.2018.1497816.

Pardo, E.G., Gil-Borrás, S., Alonso-Ayuso, A., and Duarte, A. (2024). Order batching problems: Taxonomy and literature review. *European Journal of Operational Research*, 313(1), 1–24. doi: https://doi.org/10.1016/j.ejor.2023.02.019.

Prunet, T., Absi, N., Borodin, V., and Cattaruzza, D. (2024). Optimization of human-aware logistics and manufacturing systems: A comprehensive review of modeling approaches and applications. *EURO Journal on Transportation and Logistics*, 13, 100136. doi: 10.1016/j.ejtl.2024.100136.

Roodbergen, K.J. and Koster, R. (2001). Routing methods for warehouses with multiple cross aisles. *International Journal of Production Research*, 39(9), 1865–1883. doi: https://doi.org/10.1080/00207540110028128.

Ropke, S. and Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science*, 40, 455–472. doi:10.1287/trsc.1050.0135.

Xu, S. and Hall, N.G. (2021). Fatigue, personnel scheduling and operations: Review and research opportunities. doi:10.1016/j.ejor.2021.03.036.

Zhao, X., Liu, N., Zhao, S., Wu, J., Zhang, K., and Zhang, R. (2019). Research on the work-rest scheduling in the manual order picking systems to consider human factors. *Journal of Systems Science and Systems Engineering*, 28, 344–355. doi:10.1007/s11518-019-5407-y.