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DOI
10.1016/j.procs.2024.01.063

Publication date
2023

Document Version
Final published version

Published in
Procedia Computer Science

Citation (APA)
Vermin, B. L., Abbink, D. A., & Schulte, F. (2023). Bi-Objective Job-Shop Scheduling Considering Human Fatigue in Cobotic Order Picking Systems: A Case of an Online Grocer. *Procedia Computer Science*, *232*, 635-644. https://doi.org/10.1016/j.procs.2024.01.063

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Procedia Computer Science 232 (2024) 635–644

Procedia Computer Science

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5th International Conference on Industry 4.0 and Smart Manufacturing

Bi-Objective Job-Shop Scheduling Considering Human Fatigue in Cobotic Order Picking Systems: A Case of an Online Grocer

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Abstract

Increasing online retail has resulted in increased automation in order picking systems, leading to new challenges and opportunities in task scheduling. The job-shop scheduling problem is an optimization problem essential in such systems, but existing JSP literature often overlooks workplace fatigue, which harms employees' well-being and costs U.S. employers up to €127 billion annually. In this work, we propose fatigue consideration in the job-shop scheduling problem in a cobotic order picking system to mitigate its negative effects. We present a new bi-objective mixed integer nonlinear programming problem formulation that considers worker fatigue and productivity during schedule optimisation. To put the results of simulated optimisation in perspective, we experimentally validate the fatigue model and scheduling results in a real operation. The mathematical model finds solutions that conventional single-objective optimisation cannot, allowing fractional fatigue distribution improvements more than 4x larger than the decrease in productivity they require in 53% of the considered virtual cases. The experiments show that our predictive fatigue model has an average RMSE of 2.20 kcal/min in estimating energy expenditure rates compared to heart rate measurements. It also shows a low correlation, meaning it is unfit for application. On the other hand, fatigue-conscious schedules show no clear benefit regarding measured and perceived fatigue. However, the scheduling model could also use heart rate measurements that do not show these inaccuracies. Our study highlights the need to further develop and validate the mathematical formulation and fatigue model and extend to other human factors and indirect fatigue effects.

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Peer-review under responsibility of the scientific committee of the 5th International Conference on Industry 4.0 and Smart Manufacturing

Keywords: Order Picking; Job-Shop Scheduling Problem; Human Factors; Mixed-Integer Nonlinear Programming; Occupational Fatigue; Cobotic Order Picking.

1. Introduction

Retail is shifting its business away from traditional brick-and-mortar stores and into an online setting [6]. With labour accounting for up to 55% of operational costs in order picking (OP), businesses are looking for new, more efficient

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Peer-review under responsibility of the scientific committee of the 5th International Conference on Industry 4.0 and Smart Manufacturing
10.1016/j.procs.2024.01.063

ways to prepare customers' orders [13]. By introducing automation in the OP process, retailers can increase their productivity per labour hour, allowing them to fulfil a greater demand at reduced operational costs. In the online grocery sector, which has seen increasing demand in recent years [22], automation is often only partially applied, and reliance on humans continues to exist. One operational challenge in partially automated OP systems is a combinatorial optimisation called the job-shop scheduling problem (JSP). In OP systems, the JSP describes assigning individual item picks to employees, a picking station and a time while preparing an order in a unique sequence of steps [21]. Generally, the objective is the total production time or makespan, but many other objectives exist [25]. Optimisation of the JSP in a partially automated OP system comes with additional challenges, but also ways in which the automated resources can support humans in ways previously impossible.

This work is part of a collaboration with an online grocery company. The conveyor network in company's OP system allows for flexible task assignment to order pickers ('shoppers'), who can also switch easily between (work)stations. At the same time, there can be a larger imbalance in physical workload between employees than in manual OP systems, as only a subset of items is located at each station. This storage location assignment (slotting) can lead to large, heavy or large numbers of items being picked at one station, while other stations can have much less physically fatiguing picking tasks. This fatigue affects employee well-being, productivity and the online grocer's chances of retaining shoppers.

Workplace fatigue can have costly effects on employers. Some studies estimate that the cost of fatigue-related productivity loss in the workplace is as high as 127 billion euros per year in the U.S. alone [15]. Fatigue in the workplace is a multidimensional construct in which we can identify external and occupational factors [20]. External factors include outside work activities, sleeping disorders, climate and other personal factors, while occupational factors are within the employer's control and include shift work, long hours and overtime, time on task, workload and break schedules. Not all occupational fatigue is completely avoidable, but it is possible to minimise the negative implications on the design, organisational and operational level [21].

Considering human factors (HF), such as fatigue, in work environments can simultaneously improve productivity and employee well-being [11]. HF are essential in a partial automation environment but generally not or insufficiently considered in existing operations [24]. If HF are considered, this is often done using mathematical HF models on the design level, such as workstation design [16, 23]. However, in existing facilities like the online grocers' OP system, this would require retrofitting the design level, which is not always possible and often expensive [10]. We also see that the current operational decision-making methods do not allow fatigue consideration [23]. With the opportunities that automation offers, 'cobotic' OP systems - ones with active human-robot collaboration - could then actively consider human fatigue development, mitigating its negative effects in operation [12].

In this work, we address this knowledge gap on occupational fatigue and the possibility of mitigating its negative effects through operational decision-making. We aim to understand how can we simultaneously optimise worker fatigue and productivity in the job-shop scheduling problem for cobotic order picking systems. We hypothesise that fatigue consideration in the JSP can be achieved by implementing a quantitative fatigue model in the JSP formulation and setting up a bi-objective optimisation with fatigue and productivity indicators. We expect predictive fatigue models to show some inaccuracies but still allow for appropriate fatigue mitigation in scheduling. Also, we expect fatigue-conscious schedules to lead to lower measured and perceived fatigue in real operations.

2. Related work on human factors in job shop scheduling

Implementing human factors in the JSP requires the relaxation of multiple assumptions from the basic model. Although this JSP variant has not been addressed explicitly by [25], an increasing volume of literature has been published in recent years. In Table 1, we present an overview of the implementation of HF in scheduling problems in the existing literature. The work by [19] combines learning, fatigue, recovery and motivation in a virtual job-shop scheduling problem with a combined relative goal deviation objective. The authors make many simplifications in implementing the HF models, resulting in an unrealistic version of the JSP. However, to our knowledge, they are the first to suggest multiple objectives for JSP optimisation.

[1] dive into fatigue quantification using the principle of energy expenditure and review its usability in a storage location assignment problem where both makespan and fatigue alleviation are considered. Their model does not

Article	OPF	JSP	WTHE	AV
[19]	✓	✓	✗	✗
[1]	✓	✗	✗	✗
[5]	✗	✗	✓	✗
[8]	✓	✗	✗	✓
[3]	✗	✓	✓	✓
Our Study	✓	✓	✓	✓

Table 1: Literature table of applicative HF in scheduling studies. OPF=Optimise Productivity and Fatigue, JSP=Job-Shop Scheduling Problem, WTHE=Worker and Task Heterogeneity, AV=Applicative Validation.

apply worker heterogeneity but only differentiates EE rates between activities. Their approach looks promising for an extension towards scheduling but requires real-life validation before application.

[5] and [8] both incorporate a combined fatigue-recovery model into a scheduling problem focusing on this practical application, of which the former includes worker and task heterogeneity and the latter considers multiple objectives in a real case study. Finally, [3] incorporate fatiguing, heterogeneous worker (MAEE) and task attributes and three different RA scheduling methods into a heuristic for DRC JSPs. This paper's approach differentiates operations and jobs regarding the fatiguing process. Since the individual, heterogeneous fatiguing process is captured in the recovery time parameter, and there is no notion of workload or fatigue level, the paper does not allow employers to apply these heuristics to their JSP with specific tasks and workforce characteristics. Apart from that, machine-learning approaches considering wearable sensor data have been suggested to reduce human fatigue and stress in related problems [18, 17].

The literature review shows two main research gaps in the area:

- The existing methods that can estimate fatigue through energy expenditure require live bodily measurements or have not been previously applied to or validated in settings with both worker and task heterogeneity.
- No existing works combine bi-objective optimisation of productivity and fatigue in a DRC JSP with worker and task heterogeneity.

This work fills these research gaps by applying a personalised, predictive fatigue model to a mathematical JSP formulation where real-life DRC OP system constraints are considered. Because this fatigue model has not yet been validated in a similar setting, nor has they been applied to similar scheduling problems, there is a need for real-life applicative validation of the fatigue model and resulting schedules.

3. Modelling approach

In this section, we present the selected fatigue model, followed by the mathematical JSP formulation that it was applied to. Then, we discuss the optimisation approach.

3.1. Fatigue model

Before applying the RA model, we perform the task decomposition method by [9]. For the highly similar tasks that shoppers do, this detailed task decomposition method is suitable for estimating the average EE rate during picking, though this is still a simplification of the real world. Each body movement is coupled to a specific equation dictating the energy expenditure of that task. For example, a two-arm lift with load L is represented by:

$$EE = 10^{-2}\,[0.062BW\,(h_2 - 0.81) + (3.19L - 0.52S \cdot L)\,(h_2 - h_1)] \text{ for } 0.81 < h_1 < h_2 \tag{1}$$

with BW the body weight of the shopper, h_2 the endpoint height of the lift, S the sex of the shopper and h_1 the starting point height of the lift. The formulae from [9] have been adjusted to fit our specific situation, with standard assumptions for h_1, h_2 and the pick displacement distance. Furthermore, we assume the floor is level, no pull or pushing force is required during picking or placing, and the picking height is constant. Station switching energy and energy spent waiting between picks are only considered in the experiments.

Each elemental movement is also estimated in terms of time, therefore allowing us to take the average $\dot{EE}$ during the pick action. The personal characteristics, a pick speed parameter, different item weights and walking distances ensure this calculation embodies both worker and task heterogeneity. The worker heterogeneity is also considered in the calculation of $\dot{EE}_R$, also from [9], and MAEE calculation from [7] (see 2).

$$MAEE = \begin{cases} 0.0016\,((60 - 0.55 \cdot AGE) \cdot BW) & \text{Men} \\ 0.0016\,((48 - 0.37 \cdot AGE) \cdot BW) & \text{Women} \end{cases} \tag{2}$$

3.2. Mathematical job shop scheduling formulation

In this section, we present a mathematical formulation for the scheduling problem.
Our mathematical model is based on the work by [3] and [26], but adds decision variables and constraints to improve the completeness of their formulations. The resulting attributes and assumptions of this model are:

1. Set of *shoppers* process a unique set of *order lines* for a set of *totes* on a set of *stations*.
2. All information on shoppers, stations, totes and order lines is pre-known and fixed.
3. There are no due dates or different priorities between totes or order lines.
4. Order lines are specific items to be picked per tote, which can be any item in the assortment.
5. Any shopper can pick any order line, but only on a subset of stations.
6. Totes are independent of each other; order lines are not: they are subject to precedence constraints based on pre-known item fragility categories.
7. An order line can be picked once, on only one station at a time; there is no interruption or preemption for picking.
8. Waiting is permitted between order lines.
9. Each order line has a specific processing time and rest allowance, both item- and shopper-dependent.
10. Order lines of the same tote cannot be picked simultaneously.
11. Rest allowance must be scheduled directly after picking an order line.
12. Shoppers can switch stations, which costs (travel) time.
13. Stations and shoppers only process one order line at a time and are independent.
14. No buffer, setup time, warehouse or machine availability constraints are considered.

Following the notation in Table 2, the mathematical model can be defined as follows:

$$\min \quad x\frac{C_{max} - C_0}{C_0} + (1-x)\,\frac{EE_{max} - EE_0}{EE_0} \tag{3a}$$

$$\text{s.t.} \quad C_{max} = max_{i \in \boldsymbol{I}; j \in \boldsymbol{J}_i}\left(C_{i,j}\right), \tag{3b}$$

$$EE_{max} = max_{l \in \boldsymbol{L}}\left(\sum_{k \in \boldsymbol{K}} \sum_{j \in \boldsymbol{J}_i} \sum_{i \in \boldsymbol{I}} EE_{i,j,l} \cdot \alpha_{i,j,k,l}\right), \tag{3c}$$

$$C_{i,j} = S_{i,j} + \sum_{l \in \boldsymbol{L}} \sum_{k \in \boldsymbol{K}} \left(p_{i,j,l} + r_{i,j,l}\right) \alpha_{i,j,k,l}, \tag{3d}$$

$$\sum_{l \in \boldsymbol{L}} \sum_{k \in \boldsymbol{K}} \alpha_{i,j,k,l} = 1, \qquad \forall i \in \boldsymbol{I}; j \in \boldsymbol{J}_i, \tag{3e}$$

$$\sum_{l\in\boldsymbol{L}}\sum_{k\in\boldsymbol{K}_{i,j}}\alpha_{i,j,k,l} = 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3f}$$

$$S_{i,j'} \geq C_{i,j}\cdot\beta_{TO:i,j,j'}, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i; j'\in\boldsymbol{J}_i\setminus\{j\}, \tag{3g}$$

$$\beta_{TO:i,j,j'}+\beta_{TO:i,j',j} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i; j'\in\boldsymbol{J}_i\setminus\{j\}, \tag{3h}$$

$$\beta_{TO:i,j,j'} = 0, \qquad \forall i\in\boldsymbol{I}; j=j'\in\boldsymbol{J}_i, \tag{3i}$$

$$\sum_{j'\in\boldsymbol{J}_i}\sum_{j\in\boldsymbol{J}_i}\left[\beta_{TO:i,j,j'}\right]+1 = \sum_{l\in\boldsymbol{L}}\sum_{k\in\boldsymbol{K}}\sum_{j\in\boldsymbol{J}_i}\alpha_{i,j,k,l}, \qquad \forall i\in\boldsymbol{I}, \tag{3j}$$

$$\sum_{j'\in\boldsymbol{J}_i}\beta_{TO:i,j,j'} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3k}$$

$$\sum_{j'\in\boldsymbol{J}_i}\beta_{TO:i,j',j} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3l}$$

$$S_{i',j'} \geq C_{i,j}\cdot\beta_{ST:i,j,i',j',k}, \qquad \forall i,i'\in\boldsymbol{I}; j\in\boldsymbol{J}_i; j'\in\boldsymbol{J}_{i'}; k\in\boldsymbol{K}, \tag{3m}$$

$$\beta_{ST:i,j,i',j',k}+\beta_{ST:i',j',i,j,k} \leq \sum_{l\in\boldsymbol{L}}\alpha_{i,j,k,l}\cdot\sum_{l\in\boldsymbol{L}}\alpha_{i',j',k,l}, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i; [i',j']\in\boldsymbol{J}\setminus\{[i,j]\}; k\in\boldsymbol{K}, \tag{3n}$$

$$\beta_{ST:i,j,i',j',k} = 0, \qquad \forall [i,j]=[i',j']\in\boldsymbol{J}, \tag{3o}$$

$$\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\sum_{j\in\boldsymbol{J}_i}\sum_{i\in\boldsymbol{I}}\left[\beta_{ST:i,j,i',j',k}\right]+1 = \sum_{l\in\boldsymbol{L}}\sum_{j\in\boldsymbol{J}_i}\sum_{i\in\boldsymbol{I}}\alpha_{i,j,k,l}, \qquad \forall k\in\boldsymbol{K}, \tag{3p}$$

$$\sum_{k\in\boldsymbol{K}}\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\beta_{ST:i,j,i',j',k} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3q}$$

$$\sum_{k\in\boldsymbol{K}}\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\beta_{ST:i',j',i,j,k} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3r}$$

$$S_{i',j'} \geq \left(C_{i,j}+\sum_{k\in\boldsymbol{K}}\sum_{k'\in\boldsymbol{K}}s_{k,k'}\cdot\gamma_{i,j,i',j',k,k',l}\right)\cdot\beta_{SH:i,j,i',j',l}, \qquad \forall i,i'\in\boldsymbol{I}; j\in\boldsymbol{J}_i; j'\in\boldsymbol{J}_{i'}; l\in\boldsymbol{L}, \tag{3s}$$

$$\beta_{SH:i,j,i',j',l}+\beta_{SH:i',j',i,j,l} \leq \sum_{k\in\boldsymbol{K}}\alpha_{i,j,k,l}\cdot\sum_{k\in\boldsymbol{K}}\alpha_{i',j',k,l}, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i; [i',j']\in\boldsymbol{J}\setminus\{[i,j]\}; l\in\boldsymbol{L}, \tag{3t}$$

$$\beta_{SH:i,j,i',j',l} = 0, \qquad \forall [i,j]=[i',j']\in\boldsymbol{J}, \tag{3u}$$

$$\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\sum_{j\in\boldsymbol{J}_i}\sum_{i\in\boldsymbol{I}}\left[\beta_{SH:i,j,i',j',l}\right]+1 = \sum_{k\in\boldsymbol{K}}\sum_{j\in\boldsymbol{J}_i}\sum_{i\in\boldsymbol{I}}\alpha_{i,j,k,l}, \qquad \forall l\in\boldsymbol{L}, \tag{3v}$$

$$\sum_{k\in\boldsymbol{K}}\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\beta_{SH:i,j,i',j',l} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3w}$$

$$\sum_{k\in\boldsymbol{K}}\sum_{j'\in\boldsymbol{J}_{i'}}\sum_{i'\in\boldsymbol{I}}\beta_{SH:i',j',i,j,l} \leq 1, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3x}$$

$$\gamma_{i,j,i',j',k,k',l} = \sum_{j\in\boldsymbol{J}_i}\sum_{i\in\boldsymbol{I}}\left[\beta_{SH:i,j,i',j',l}\cdot\alpha_{i,j,k,l}\cdot\alpha_{i',j',k',l}\right], \qquad \forall i'\in\boldsymbol{I}; j'\in\boldsymbol{J}_{i'}; k\in\boldsymbol{K}; k'\in\boldsymbol{K}\setminus\{k\}; l\in\boldsymbol{L}, \tag{3y}$$

$$\gamma_{i,j,i',j',k,k',l} = 0, \qquad \forall k=k'\in\boldsymbol{K}, \tag{3z}$$

$$\beta_{TO:i,j,j'}\cdot f_{i,j} \leq f_{i,j'}, \qquad \forall i\in\boldsymbol{I}; j,j'\in\boldsymbol{J}_i, \tag{3aa}$$

$$S_{i,j} \geq 0, \qquad \forall i\in\boldsymbol{I}; j\in\boldsymbol{J}_i, \tag{3ab}$$

$$\alpha_{i,j,k,l},\beta_{TO:i,j,j'},\beta_{ST:i,j,i',j',k},\beta_{SH:i,j,i',j',l},\gamma_{i,j,i',j',k,k',l}\in\{0,1\}, \qquad \forall i,i'\in\boldsymbol{I}; j\in\boldsymbol{J}_i; j\in\boldsymbol{J}_{i'}; k,k'\in\boldsymbol{K}; l\in\boldsymbol{L}. \tag{3ac}$$

Here (3a) is the bi-objective to minimise, a combination of C_{max} and EE_{max} coupled by weight parameter x. This objective is a weighted sum with fractional single-objective deviation. There are better methods to investigate the trade-off between two objectives, but this method allows estimation of a Pareto front without many repetitions of the optimisation, which is especially relevant for NP-hard problems [14, 2]. The two objectives C_{max} and EE_{max} are

Notation	Description
i, i', i''	Tote index
j, j', j''	Order line index
k, k', k''	Station index
l, l'	Shopper index
$\boldsymbol{I}$	Set of totes
$\boldsymbol{J}$	Set of order lines per tote, $\boldsymbol{J}_i$ is a set of all order lines for tote i
$J_{i,j}$	jth order line of tote i
$\boldsymbol{K}$	Set of stations
$\boldsymbol{K}_{i,j}$	Set of stations where order line $J_{i,j}$ can be picked
$\boldsymbol{L}$	Set of shoppers
$C_{i,j}$	Completion time of order line $J_{i,j}$
C_{max}	Maximum completion time, makespan
EE_{max}	Maximum sum of required energy expenditure for all individuals
Parameters	
C_0	Optimal value for C_{max} if only optimising for C_{max} (or $x = 1$)
EE_0	Optimal value for EE_{max} if only optimising for EE_{max} (or $x = 0$)
$EE_{i,j,l}$	Energy expenditure for order line $J_{i,j}$ when shopper l is executing it
$f_{i,j}$	Item fragility category of order line $J_{i,j}$
$p_{i,j,l}$	Processing (picking) time of order line $J_{i,j}$ when shopper l is executing it
$r_{i,j,l}$	Recovery time for shopper l after picking order line $J_{i,j}$
$s_{k,k'}$	Switching time between station k and k'
x	Bi-objective weight parameter
Decision variables	
$S_{i,j}$	Starting time of order line $J_{i,j}$ (sec.) measured from start of operation ($t = 0$)
$\alpha_{i,j,k,l} \in \{0, 1\}$	1 if station k and shopper l are selected to process order line $J_{i,j}$, 0 otherwise
$\beta_{TO:i,j,j'} \in \{0, 1\}$	1 if tote i order line $J_{i,j}$ is performed right before $J_{i,j'}$, 0 otherwise
$\beta_{ST:i,j,i'j',k} \in \{0, 1\}$	1 if order line $J_{i,j}$ is performed right before $J_{i',j'}$ on station k, 0 otherwise
$\beta_{SH:i,j,i',j',l} \in \{0, 1\}$	1 if order line $J_{i,j}$ is performed before $J_{i',j'}$ by shopper l, 0 otherwise
$\gamma_{i,j,i',j',k,k',l} \in \{0, 1\}$	1 if shopper l moves from station k to k' to pick order line $J_{i',j'}$ after picking $J_{i,j}$, 0 otherwise

Table 2: Notations, parameters and decision variables for the DRC JSP formulation with fatigue consideration.

defined in (3b) and (3c). (3d) calculates the value of auxiliary variable $C_{i,j}$. Constraint (3e) ensures every order line is executed once by one shopper and on one station, while (3f) specifies the subset of stations where this can be done.

Constraints (3g)-(3l), (3m)-(3r) and (3s)-(3x) are sequencing constraint sets on three different levels with high similarity: tote, station and shopper. First, (3g) ensures no two order lines belonging to the same tote can be picked simultaneously, no matter which station and shopper are involved. Therefore, the starting time of that tote's order line picked next is at least the completion time of the previous one. Constraints (3l)-(3l) then define sequence decision variable β_{TO}. Second, (3m)-(3r) ensure the same as (3g)-(3l), but on the station level and with the notion that the order lines are indeed picked at that station. Third, (3s)-(3x) do this on the shopper level, thereby switching the roles of $k, \boldsymbol{K}$ and $l, \boldsymbol{L}$. One extra addition is the station switching time $s_{k,k'}$, for which we require (3y) and (3z) to define switch decision variable γ. Finally, (3aa) ensures that order lines within one tote are picked in the order of the fragility category, and (3ab) and (3ac) define the types of the decision variables.

4. Experimental study

We perform experiments to validate the fatigue model and the resulting schedules simultaneously. The experiments are done during normal picking operations in the online grocers' OP system, a real-life facility still in ramp-up. This can cause demand fluctuations and disturbances that require constant monitoring, therefore allowing only two participants to be tested at once. The participants are healthy employees familiar with the OP system (> 1 month of

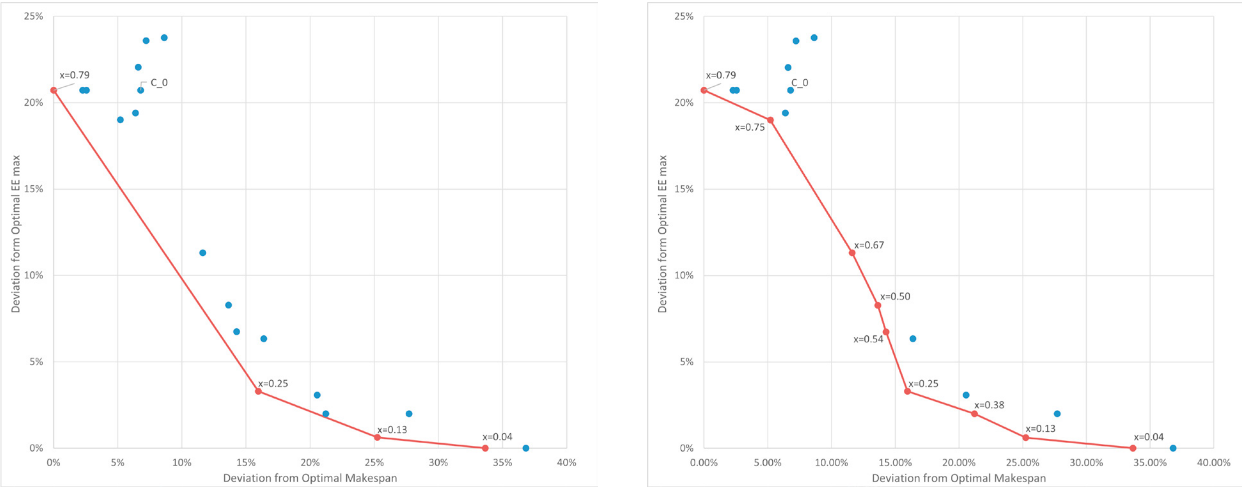

Fig. 1: Two different shapes for the Pareto front estimate without globally optimal solutions.

experience), so learning effects are minimised. The mathematical model includes worker heterogeneity, so we try to include this in the data as much as possible. Therefore, we randomly select shoppers from the working schedule a day before the tests and ask them to participate. We expect 20 participants to be sufficient to represent the variance in the entire employee pool.

4.1. Scheduling and optimization experiments

We solve the presented MINLP using SCIP, or Solving Complex Integer Problems. SCIP uses a spatial branch-and-bound algorithm with linear relaxations. This allows the solver to find global optima for non-convex MINLPs [4]. SCIP version 8.0.3 was installed on Windows Subsystem for Linux and executed on an Intel 10700F octa-core 2.9/4.7GHz processor with 16GB DDR4 RAM.

Because of our exact solver, we only run small virtual problem instances through our scheduling model. We find globally optimal solutions within 6000 seconds of run time until the number of decision variables exceeds roughly 2,500. This is already the case for problem instances with 3 totes, 3 order lines per tote, 3 stations and 2 shoppers, a problem size tiny in comparison to real-life problem sizes. However, even for these small problems, we can identify some key outcomes of our developed approach.

Larger problem instances, which have more decision variables and thus more degrees of freedom in scheduling, are seen to deliver more feasible solutions in optimisation, but these solutions are not guaranteed to be globally optimal. In general, this means there are no solutions that can be guaranteed to be Pareto-optimal. If we only look at the solutions that are not dominated by any other known solution - meaning they could be non-dominated, but cannot be guaranteed as such - we can also estimate the Pareto front in this case, as shown in Figure 1. However, the front can be drawn in multiple ways, even in a concave shape.

4.2. Empirical fatigue model experiments

First of all, men and women of different ages are evenly represented in our population sample. Also, their heart rate records show no remarkable anomalies in comparison to population databases. Predicted $\dot{EE}_R$ and $MAEE$ values vary between participants. We also see that $\dot{EE}_R$ and $\dot{EE}_{orders}$ (for the same order data) increase slightly with the $MAEE$, but that the $MAEE$ values tend to relatively exceed these by a larger margin for higher $MAEE$ and that these relations differ per individual.

Figure 2 shows visually the distribution and relative relation between the different estimates for $\dot{EE}$. Generally, we see that the individuals that are below the median in one of the box plots are also below the median in the others and vice versa, especially when comparing $\dot{EE}_{picks}$ and $\dot{EE}_{orders}$.

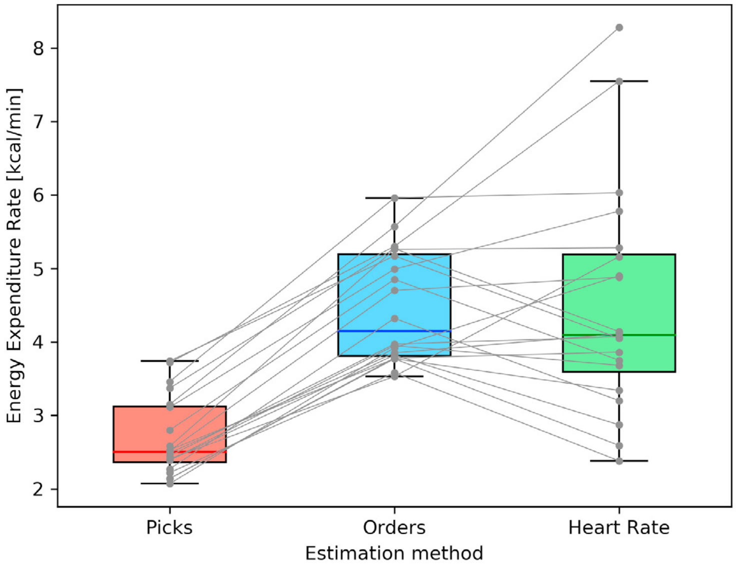

Fig. 2: Three interconnected box plots representing the average values from the different estimation methods. Each line represents one individual during the tests.

As we treat $\dot{EE}_{HR}$ as the most accurate estimate of the energy expenditure rate in these circumstances, we evaluate the accuracy of $\dot{EE}_{orders}$ and $\dot{EE}_{picks}$ by comparing their estimates to this value. For $\dot{EE}_{orders}$, this results in a root root-mean-square error (RMSE) of 1.14 kcal/min, while $\dot{EE}_{picks}$ has an RMSE of 2.20 kcal/min. These values are in agreement with the visual representation in Figure 2.

5. Discussion

Even though our methods only allow for a few unique non-dominated solutions to be found, we are able to improve the energy expenditure distribution in comparison to single-objective optimisation solution 'C_0'. This choice would depend on managerial insights, but the steep Pareto front line pieces that we found indicate considerable potential for implementation. This is in accordance with our hypothesis.

The results of the empirical study show a good selection of participants for this study. Also, the differences and relations between $MAEE$, $\dot{EE}_R$ and $\dot{EE}_{orders}$ show the value of fatigue-conscious scheduling, also highlighting the importance of our personalised fatigue modelling approach over the assumptions made by [1]. However, our predictive fatigue model shows large inaccuracies in estimating the fatigue throughout all experiments. This is the case on a shift level but also for 10-minute intervals. A first valid suspicion could relate these inaccuracies to the highly volatile pick demand, but our results show no clear relation between the pick demand and estimation accuracy. This contradicts our expectations of the estimation method's performance.

Shoppers do much more than just order picking, such as pallet loading, cleaning and opening boxes. We estimate that about 25% of the shift is not spent according to our task decomposition description. However, the task intensity of the other tasks, we believe, is similar to that of picking. This would explain the better estimations of $\dot{EE}_{orders}$, as this assumes a continuous picking workload. Furthermore, lots of operational challenges occurred during the experiments, such as system downtime and shopper reassignment, troubling the experimental circumstances.

These factors could also have influenced the schedule validation results, where we see no clear differences between scenarios or the two groups of participants in terms of $\dot{EE}_{HR}$ or the qualitative fatigue ratings. Therefore, we cannot conclude that the positive results from our modelling study immediately translate to real-life applications.

6. Conclusion

Increasing automation in the work environment can offer new solutions to the operational challenges in partially automated OP systems. Although methods exist to quantify fatigue and consider it in a scheduling context, these still need to find their way into real-life applications. This work presents a detailed formulation for the job-shop scheduling problem in a robotic order picking system, considering physical workload distribution and total makespan simultaneously. Thereby we bridge the gap between theoretical scheduling problem approaches and operational reality in the context of human fatigue. Our work establishes the first steps towards human fatigue consideration in scheduling for real-life operations.

- We find that energy expenditure-based fatigue models can best be applied in scheduling problem formulations. In combination with the rest allowance principle, this allows for a personalised approach to fatigue in a scheduling context. The applied predictive fatigue model allows for detailed task decomposition without prior measurements, able to evaluate energy expenditure requirements for various tasks. This is in accordance with our hypothesis.
- Our modelling study shows that the proposed bi-objective JSP formulation can successfully generate schedules for partially automated OP systems while considering fatigue and productivity. As expected, the results are promising for application, although our results are limited to small problem instances. We argue that the mathematical formulation could benefit from a different solution approach, without the need for reformulation.
- Our empirical study shows that the applied predictive energy expenditure model was inaccurate in estimating energy expenditure rates in a real operation and that heart rate sensors are a more viable approach at this time. Also, we find no significant changes in measured or qualitative fatigue after applying the generated fatigue-conscious schedules, in contrast with the results from the modelling study. Both results are in contrast with our expectations prior to this research and offer opportunities for further research.

These findings have practical implications for scheduling in real-life operations, providing management with alternative schedules that consider productivity and employee physical strain. This work sets the first steps towards human fatigue consideration in scheduling for real-life operations and opens up avenues for further research in this field. This work has several limitations, which we summarise with accompanying suggestions for future research: The exact optimization model does not yield solutions for large-scale instances. Appropriate bi-objective heuristics may help gain a better understanding by considering more realistic problem sizes. We choose to model energy expenditure, the precursor of fatigue, and therefore not fatigue itself. Other ergonomic models may better approximate human fatigue. Moreover, the conducted real-word experiment was also limited in size and should be validated with more participants under varied conditions.

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