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A two-stage stochastic model for picker allocation problem in warehouses considering the rest allowance and picker's weight

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C H R O N I C L E

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A B S T R A C T

Order picking (OP) is a critical yet time-consuming and labor-intensive warehouse operation within the supply chain. In picker-to-part systems with high demand, pickers are exposed to fatigue due to the excessive repetition of picking activities, which results in high human energy expenditure. The literature indicates that energy expenditure depends on the picking activity and the worker's attributes, such as pickers' weight, gender, and age. Studies have shown that as the weights of individuals increase, the energy consumed for the same task increases. This study proposes a two-stage stochastic programming model that minimizes assignment and overtime costs while avoiding excessive fatigue levels for pickers by incorporating rest allowance into the picking tour time. In the first stage, the number of pickers required is decided. In the second stage, orders are assigned to pickers considering uncertain energy expenditure. The two-stage stochastic programming model is solved by the sample average approximation algorithm. Results show that both OP cost and the number of pickers required to fulfill an order increase when the picker's weight exceeds 80kg. In allocating orders, pickers weighing less than 80kg should be assigned to orders with more items, such as those containing 4- or 5-items. Conversely, pickers weighing more than 80kg should be assigned to orders with fewer items, like those containing 2- or 3-items, to avoid fatigue side effects.

1. Introduction

Companies must effectively plan their warehouse activities to provide customers with high-quality service and reduce logistics costs. OP is one of the critical warehouse activities that requires more time and workforce than other activities. In OP, pickers retrieve items from storage units in response to customer demand. According to De Koster et al. (2007), OP costs are estimated to be as high as 55% of the overall warehouse operating costs. Therefore, any underperformance in OP operations can lead to higher financial loss for warehouses and, consequently, the whole supply chain. Many companies prefer manual systems operated by human order-pickers due to human flexibility in responding to short-changing product portfolios and handling order heterogeneity (Grosse et al., 2017). Estimates show that almost 80% of warehouses rely on the picker-to-part systems (De Koster et al., 2007; Grosse et al., 2017), where pickers retrieve items from storage shelves by walking along the warehouse without using any additional lifting equipment/vehicle. Considering the dominance of human factors in warehouses, this study focuses on pickers' well-being and system performance concurrently while assigning orders to pickers. During the OP route, workers perform repetitive tasks (e.g., stooping, squatting, or lifting) in awkward body positions and under high stress to ship orders on time. Even though lightweight items are handled, excessive item-picking accumulates significant energy expenditure that causes fatigue (Al-Araidah et al., 2021; Grosse et al., 2017). Fatigue is a sense of overwhelming tiredness, a feeling of exhaustion that affects individuals' physical or mental health, and it causes a reduction in human physical performance (Comi et al., 2001; Gawron et al., 2000). When pickers' fatigue has not been considered in OP operations, many economic losses (e.g., delays due to wrong or incorrect items) or ergonomic risks (e.g., injuries and musculoskeletal disorders) occur (Vanheusden et al., 2020). The direct link between economic and ergonomic aspects of operations planning is presented by Finco et al. (2020), where work-related musculoskeletal disorders sum up to 160 million, decreasing the gross national product by 3.94% worldwide.

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Several attempts have been made in the literature to incorporate personal differences in estimating workers' energy expenditure to prevent fatigue effects. For instance, the impact of the worker's age on energy expenditure is integrated into mixed-model assembly line balancing problems (ALBP) (see Calzavara et al., 2020; Finco et al., 2021). Pickers' weight is another feature that strongly affects energy expenditure; as weight increases the amount of energy consumed increases (Al-Araidah et al., 2021). Therefore, pickers' weight must be considered in OP planning to achieve acceptable ergonomic levels. For instance, the duration of rest time can be dependent on pickers' weight as there is a positive relationship between weight and energy consumption (Al-Araidah et al., 2021). According to the Health briefly Report OECD (2021), overweight and obese individuals constitute a significant portion of the population; the ratio is 59.6% on average for OECD countries, and Mexico, Chile, and the US are the top three countries suffering from this problem.

Higher ratios of overweight individuals call upon management to account for challenges associated with weight problems in workplaces where manual operations are intensively performed, such as picker-to-parts manual picking systems. The importance of workforce allocation in providing practical solutions to industry needs was addressed by Van Gils et al. (2018). In order to contribute to the weight challenge in workplaces, this study focuses on pickers' weight as a responsible personal factor for the variation in energy expenditure for manually operated warehouses. In many OP studies, calculations depend on the metabolic energy expenditure of the "average people". Nevertheless, Sgarbossa et al. (2020) highlight that the design of human-centered systems necessitates personalized solutions that consider individual differences. In this context, incorporating physical metrics of pickers has proven to be highly effective in assigning the most suitable tasks to each picker, as discussed by Matusiak et al. (2017) and Katiraee et al. (2019). The uncertainties originating from personal differences pose a burden on balancing the physical effort or fatigue level among workers. Deterministic approaches are adapted for ease of use in practice, assuming more stable environments to provide good approximations. However, in the case of high fluctuation in order configuration and associated responsive actions (e.g., searching, grasping, carrying), deterministic models are inadequate to cover the system's randomness and may provide managers with wrong conclusions. Motivated by Van Gils et al. (2018), this paper incorporates the energy expenditure of pickers into the worker assignment problem to avoid fatigue. Specifically, this research deals with the worker assignment problem, which is deciding the number of order pickers employed and the workforce allocation based on pickers' energy expenditure concerning their weight and OP costs. In this study, using energy expenditure as an index to calculate the order picker's fatigue level, the following research questions were investigated: RQ1) How does the picker's weight impact the worker assignment problem? and RQ2) How should orders be assigned to pickers considering their body weight so that no excessive fatigue effects are observed? To answer these questions, a novel two-stage stochastic programming model that minimizes the total expected assignment and the overtime cost considering the energy expenditure depending on the order configuration and picker's weight was developed. In the first stage, the optimal number of order pickers was decided, and in the second stage, pickers were assigned to orders to minimize overtime. It is important to mention that the model aims to provide a better fit for order-to-picker assignments and provide practical implications for warehouse managers in the worker assignment problem. At the same time, this study avoids discriminating against workers because of their weight.

The contribution of the model to the literature is in the following aspects: i) introduction of the rest allowance (RA) concept into the order-to-picker assignment problem to avoid fatigue, ii) consideration of the uncertainties in energy expenditure in the OP planning problem, iii) incorporation of individual differences as a function of energy consumption and picking-time to provide a better match between orders and pickers, and iv) provision of a daily decision support system that aids managers in assigning orders aiming to minimize the total cost and avoid excessive fatigue levels.

The organization of the manuscript is as follows: Section 2 provides a review of state-of-the-art studies. Section 3 presents the problem. The two-stage stochastic programming model is discussed in Section 4. Section 5 presents the solution method, which is the sample average approximation method. The numerical studies on order configuration and physical differences to gain managerial insights are provided in Section 6. Finally, Section 7 presents the general results and insights from numerical studies while concluding the paper.

2. Theoretical background and state-of-the-art

This section discusses the literature focusing on i) energy expenditure, fatigue, and RA and ii) workforce allocation in order picking in two subsections, 2.1 and 2.2.

2.1. Energy expenditure, fatigue, and rest allowance

Work-related musculoskeletal disorders occur when the physical needs of the work exceed the operators' capabilities. From an ergonomic perspective, to prevent operators from musculoskeletal disorders, many ergonomic metrics, such as OCRA, NIOSH, or RULA, have been used in the literature (e.g., Gebennini et al., 2018). With technological advances, these metrics have been deployed for real-time posture monitoring to provide ergonomic solutions to warehouses or manufacturing environments. To benefit from these solutions, sensors should be placed on the upper and lower parts of the body so that the postures of the operators can be fully captured and monitored, which is not always an easy or economical solution (Battini et al., 2014). Likewise, measuring the operators' energy expenditure helps to assess the related ergonomic aspects of the job to improve human efficiency. Energy expenditure helps understand the physical stress required to perform a task objectively

(Garg et al., 1978). It has been used as an ergonomic metric for comparing the effort paid for the execution of various tasks and monitoring the fatigue level of the individuals. Fatigue can be in psychological and physical forms (Gawron et al., 2000). This study considers physical fatigue due to executing a task with an applied force for a particular time. Various approaches assess physical fatigue depending on whether the complete body or specific body parts are used. OP operations, such as walking or carrying, typically force workers to use their whole body rather than specific muscles. To measure the general fatigue raised, Garg, Chaffin, & Herrin (1978) proposed an approach that depends on dividing the work into simple tasks and then calculating the energy expenditure for every task and maintenance of the postures depending on individual characteristics, such as age, gender, and body weight. The accumulated energy expenditure of all tasks presents the total energy expenditure for executing that work. This method is prevalent in literature as it is easy to calculate and integrate individual characteristics.

There should be a comparison between energy expenditure during task execution and the maximum acceptable energy expenditure (MAEE), which is the highest (maximum) energy consumption level, a.k.a. maximum aerobic capacity, for a human to avoid fatigue during work (Åstrand, 1967). In the literature, MAEE has been recommended at 33% of an individual's maximum energy expenditure (NIOSH, 1981). When MAEE is exceeded, workers are subjected to expedited fatigue. In response, the RA concept, which suggests giving additional break time to operators to rest and prevent fatigue effects, is introduced. Even though multiple approaches are deployed to determine RA, many require collecting various measures in the industrial context, which is not always a practical solution. We selected the model proposed by Price (1990) due to its prevalent usage, adherence to practical implications, and ease of use. Based on the formulation in Price (1990), RA occurs when the metabolic energy expenditure during task execution exceeds the MAEE as follows in Eq. (1):

$$RA = \max\left\{0, \frac{EE_{work} - MAEE}{MAEE - ET_{rest}}\right\} \tag{1}$$

where EE_{work} and ET_{rest} are the metabolic energy expenditure during work and rest time, respectively. In this formulation, it is important to notice that RA is defined as a percentage of working time. For instance, 10% RA for a 10-minute job means the worker needs an additional one minute to rest adequately. After providing the theoretical background, below presents the studies that attempt to integrate energy consumption and fatigue as ergonomic assessment metrics. Both metrics were utilized in manufacturing problems (e.g., ALBP and job scheduling) and designing warehouse operations. Battini, Delorme, et al. (2016a) were the first to introduce the energy expenditure concept as a human factor metric in ALBPs. They proposed a multi-objective optimization model that considers the time and ergonomic sides of the assembly line. The Pareto frontiers were presented to help practitioners understand how the solution to balancing problems affects productivity and ergonomics. Similarly, Abdous et al. (2018) developed a linear multi-objective mixed integer programming (MIP) model that aimed to optimize the number of workstations and minimize the fatigue level of the operators for ALBP. Based on the results, the increase in the number of workstations led to an exponential decrease in the fatigue level of the workers. The study helped balance the assembly line with less worker fatigue. Similarly, Abdous et al. (2022) developed a multi-objective MIP model that considered assembly line workers' fatigue levels while minimizing the number of stations for the ALBP. Numerical studies showed that improving ergonomics is not necessarily translated as higher tact time or additional workstations. Ferjani et al. (2017) worked on assigning multi-skilled workers in manufacturing, considering the fatigue effect. The fatigue levels of the workers were dynamically calculated through an exponentially increasing indicator, which is a function of time. A simulation-based optimization is proposed to assign workers considering their fatigue levels and skills to minimize the mean flow time of jobs. In order to reduce excessive fatigue levels, Finco et al. (2020) introduced the RA concept for the ALBP to improve the performance of the assembly lines, considering both economic and ergonomic aspects. In their study, they developed a MIP model to minimize the smoothness index to ensure a similar distribution of work among stations. Additionally, a heuristic algorithm was proposed when the MIP model fell short of computation due to the large number of tasks assigned to the stations.

Additionally, although workers perform the same task, the MAEE varies for their physical features. In this regard, Dalle Mura and Dini (2019) developed a model for solving ALBP regarding workers' skills and capabilities, which were assessed through anthropometric and physiological characteristics. Their study showed that energy expenditure differed from human to human regarding personal features, such as gender, age, and weight; thus, incorporating those differences in ALBP can improve productivity and human factor-related issues. Similarly, Katiraee et al. (2021) presented a bi-objective model focusing on cycle time and physical workload minimization by introducing the Worker Tasks Categorization Matrix for ALBP. The Borg scale was used to assess physical effort considering personal features and perceptions. Results showed that the worker assignment plan that avoids overwhelming physical workload with slightly increased cycle time was applicable. Likewise, Finco et al. (2021) considered "age" as an individual factor that impacts the acceptable energy expenditure of mixed model assembly line workers. First, a linear model was built to minimize cycle time for ALBP. Then, a sequencing model was developed to minimize the workload calculated through RA integration concerning workers' age. In addition to ALBP, some papers consider the fatigue level of the workers for job scheduling problems. Berti et al. (2021) showed how fatigue and work experience could be included in scheduling problems to fit jobs and workers better considering RA for workers. Results showed that ignoring RA can cause critical performance decline, which decreases system performance. Individual rest breaks should be determined depending on individual features like age. Recently, Battini et al. (2022) developed a multi-objective job rotation scheduling model that considered socio-technical factors: workers' experience, physical capacity, postural ergonomic risks, noise and vibration exposure, and workers' boredom. The study aimed to determine the best job assignment and provide workers with individualized rest plans. The results showed that flexible work plans help workers improve their capabilities through acquiring experience in various tasks with less perceived fatigue and boredom and increased satisfaction and motivation.

To our knowledge, Al-Araidah et al. (2021) is the first study that mentioned the RA concept for the OP problem. The study presented a Monte Carlo simulation model to estimate the average energy expenditure of female order pickers working in a large warehouse regarding their weights and walking speed. The simulation results presented a significant increase in energy expenditure levels of the order pickers above the average weight. The study clearly stated that warehouse operation planning should consider this difference in pickers' well-being and operational performance.

2.2. Workforce allocation

The primary focus of the workforce allocation in OP operations was on pick-time reduction and associated delays. Henn (2015) studied combined order batching and sequencing problems for manual picker-to-parts OP systems. The study proposed a variable neighborhood descent approach and a variable neighborhood search as solution methods for the problem and showed that both methods achieved high-quality solutions. Numerical studies revealed that both methods improved warehouse management and increased customer satisfaction regarding on-time order shipment. Similarly, Scholz et al. (2017) developed a mathematical model for the joint order batching, assignment, sequencing, and routing problems to minimize total tardiness. Due to the exponential increase in solution time regarding the number of orders, a variable neighborhood descent approach was introduced for larger-size problems. Their model outperformed other state-of-the-art solution approaches, and a considerable reduction in total tardiness was achieved.

Hong et al. (2012) presented an integrated order batching and sequencing problem to minimize the total order retrieval time, considering congestion delays during the picking tour. They developed an MIP model for the exact solution and introduced a simulated annealing procedure for large-scale problems. Results showed that decreasing the picker blocking improved order retrieval time by 5-15%. Matusiak, De Koster, & Saarinen (2017) developed a model for combined order batching, routing, and picker assignment problems for picker-to-parts systems to minimize the total retrieval time regarding the properties of the batches and the skills of the pickers, such as agility, driving skills, picking high items, picking from a high level, and picking large volume of batches. The problem was solved using a heuristic approach with the adaptive large neighborhood search algorithm. Based on the numerical study, incorporating the picker skills into the OP planning problem led to a 10% reduction in total order processing time. Zhang et al. (2017) studied online order batching and assignment problems with multiple pickers to ensure an impartial workload among pickers while minimizing the maximum completion time of the orders. A hybrid rule-based algorithm that considered the fixed time window batching rule and the number of arrived orders during the fixed time window was proposed to solve the problem. The algorithm's efficiency was shown under various uncertain demand scenarios, picker quantity, and order arrival rate. Their results showed that, with reasonable picking capacity and number of pickers, picking efficiency and employee availability can be enhanced while reducing employment and facility expenses.

To minimize tardiness, Van Gils et al. (2019) developed a model incorporating three order picking problems: batching, picker routing, and picker scheduling. An iterated local search algorithm was efficient in solving the integrated problem. However, human factors were not included in these three decision problems. The authors also pointed out that human factors, especially incorporating individual capabilities into a conjoint OP problem, were crucial in reducing on-time delivery and relevant to real-life OP planning. Few studies have incorporated human factors in workforce allocation for OP. Moussavi (2018) proposed a multi-objective model that aimed to (i) minimize the maximum physical workload of the operators, (ii) decrease cycle time, and (iii) balance the workload among operators. For solving the problem, linear aggregation and ε -constraint methods were used. Gebennini et al. (2018) integrated job scheduling and assignment problems considering the walking cost and ergonomic aspects, i.e., physiological, and biomechanical measures for manual lifting activities. The study employed the NIOSH index to evaluate the associated lifting operations, and the metabolic cost of walking was calculated according to Garg, Chaffin, and Herrin (1978). A MIP model was proposed for solving the joint problem. Battini et al. (2017) proposed a new procedure that can be used to assess the ergonomic effort put forward by the order pickers in the warehouse so that additional effort needed for the pickers could be calculated considering human availability (e.g., absence due to injury, sick leave - presence) and RA. The study compared two case studies where additional effort was fulfilled through indirect workers, and no indirect workforce was allowed regarding ergonomic cost savings. Results showed the benefit of employing indirect workers when an additional effort was needed. Although not directly linked with workforce allocation, Battini et al. (2016b) have worked on the storage assignment problem that decides on the positions of the items on the storage shelves to minimize the picker's energy consumption and picking time. They found that optimal positions of the items on the shelves varied significantly for two objective functions when the shelves had short aisles or when any high vertical movement was needed to retrieve items. On the other hand, for longer aisle warehouses the optimal solution was almost the same for both objectives.

Table 1 summarizes the studies that focus on workforce allocation in OP systems. According to Table 1, almost all studies incorporate pick time as a deterministic parameter. However, pick times are uncertain and change over time. Another insight we gain from Table 1 is the scarcity of studies considering the ergonomic aspects of the problem. Additionally, none of these studies took into account individual differences. Human-centered approaches that envision inter-individual differences are highly suggested for future research areas (Sgarbossa et al., 2020). Especially for OP planning, De Lombaert et al. (2022) addressed the urgent need for solutions to work rate variation and personal features. Inspired by Sgarbossa et al. (2020) and De Lombaert et al. (2022), in this study, we developed a two-stage stochastic optimization model that considers uncertainty originated by weight as a physiological measure and OP tour time.

Table 1
Summary of the literature

Author	Pick time	Human Factors	Objective	Solution Method
Hong, Johnson, & Peters (2012)	Stochastic/ Deterministic	-	Minimize the total order retrieval time	MIP Simulated annealing
Henn (2015)	Deterministic	-	Minimize the total tardiness	Variable neighborhood descent Variable neighborhood search
Scholz, Schubert, & Wäscher (2017)	Deterministic	-	Minimize the total tardiness	Variable neighborhood descent
Matusiak, De Koster, & Saarinen (2017)	Deterministic	Skills of the pickers	Minimize the total order retrieval time	Adaptive large neighborhood search
Zhang et al. (2017)	Deterministic	-	Minimize the maximum completion time of the orders	Heuristic Hybrid rule-based algorithm
Battini et al. (2017)	Deterministic	Risk (OWAS index) Physical effort, fatigue	Additional effort estimation	Simulation
Gebennini et al. (2018)	Deterministic	Physiological and biomechanical measures for manual lifting (NIOSH index)	Minimize walking costs and ergonomic effort	MIP
Moussavi (2018)	Deterministic	Workload per picker	Minimize the maximum physical workload of the operators Decrease cycle time Balance the workload	Epsilon-constraint method
Van Gils et al. (2019)	Deterministic	-	Minimizes the total order pick time	Iterated local search algorithm

3. Problem description

This study deals with lightweight item picking for the picker-to-part OP system for a traditional warehouse that includes parallel racks with a centralized pick-up and drop-off point (I/O). The picking tour starts from the I/O point as the picker receives the order notice and ends when all the items are dropped off at the same point I/O. OP tour time and associated energy expenditure data from a former work (Al-Araidah et al., 2021), which deployed a Monte Carlo simulation model to fulfill 10,000 orders, were used. Each order included 1 to 5 uniformly distributed items in that study, shortly called order configuration. Those items were assumed to be stored in locations numbered 1-720. The size of each stock location was 0.5(width)×0.5(depth)×0.3(height) meters, and all were in a total of 6 compartments. Picking times of gathering items from heights of 0.3, 0.6, 0.9, 1.2, 1.5-, and 1.8-meters compartments were assumed to be 4s, 4s, 2s, 2s, 4s, and 4s, respectively. Travel times were calculated considering the walking speed between 0.2 and 1.8 m/s. Then, total tour times were computed according to Tompkins et al. (2010), where travel and pick times accounted for 65% of OP tour time. During the OP tour, pickers were assumed to squat, stoop, arm lower, hold, carry, stand, and sit. The energy expenditure for each activity was calculated by Garg, Chaffin, and Herrin (1978), considering their physical measures. The study simulated the OP process considering a range of body weights (40 - 100 kg), order configuration (1-5 items), walking speed (0.2 and 1.8 m/s), item weight (0.25, 0.5, or 1.0 Kg) and allowable occupational physical work capacity to investigate the change in times (distance/speed) and energy expenditure for each OP tour. Building upon the statistics gained from the Monte Carlo simulation, the problem is to decide on the picker assignment considering the energy expenditure of the workers based on their weight. Following, we aim to investigate how the variation in weight impacts the assignment.

4. Problem formulation

Inspired by the Stochastic Generalized Assignment Problem (SGAP), this study proposes a new stochastic MIP model to decide the number of order pickers and job assignments under uncertain OP tour time and energy expenditure depending on pickers' weight. In SGAP with simple recourse, jobs must be assigned to machines to minimize the cost of assignment and overtime under uncertain working times. In the formulation, we interchangeably use the terms "orders" for "jobs" and "pickers" for "machines." Each order is assigned to only one picker and consumes a stochastic amount of OP tour time for order preparation needed for retrieving orders from warehouses. Depending on many factors, such as location or order configuration, OP tour time varies. Thus, tour time is a random variable. Both the fluctuation in order tour time and weight of the picker impacts the energy expenditure (Kcal/min) for OP, which is another random variable. Building upon SGAP, considering uncertain OP tour times and energy expenditure, the objective is to assign orders to pickers to minimize the cost of assignment and overtime while fatigue is eliminated. First, the deterministic version of the problem, a core model, is presented in Section 4.1. Next, by extending the model to incorporate random OP tour time and energy consumption, a two-stage stochastic model is developed in Section 4.2. The main assumptions of the model are as follows:

There are number of O orders;

There are number of W pickers;

For the deterministic model in Section 4.1, each order has a deterministic OP time t_i and an energy expenditure $\tilde{e}_{ij}$. OP time t_i is a function of order configuration, walking speed of the picker. The deterministic values are replaced by their uncertain counterparts in Section 4.2, in which each order has an uncertain OP time $\tilde{t}_i$ and energy expenditure $\tilde{e}_{ij}$;

No order batching is allowed. Starting from the I/O point, each picker starts the OP route and finalizes the tour in the I/O point after all the items in the order are collected;

OP time includes all picking-associated activities, such as searching, grasping, and carrying items;

Pickers are assumed to expend energy to maintain a standing posture throughout the tour;

RA is calculated for each order and picker, and added to the OP time;

There are enough items in storage locations to fulfill the daily demand.

4.1. Deterministic model

This section presents the sets, parameters, and mathematical formulation of the deterministic model as follows:

Sets

I : set of orders, $I = \{1,...,o\}$

J : set of pickers, $J = \{1,...,w\}$

K : set of item counts in the order, $K = \{1,...,\kappa\}$

S_k subset of orders that include k items, $S_k \subset I$

Parameters

a : assignment cost [dollars per 8 hours]

p : overtime penalty [dollars per minute]

t_i : OP tour time of order i [minute]

t_{limit} : regular working hours [8 hours]

e_{ij} : energy expenditure of order picker j to prepare order i [Kcal/min]

e_{limit} : MAEE for a picker [Kcal/min]

e_{rest} : energy expenditure during rest [Kcal/min]

Decision variables

x_{ij} : 1 if order i is assigned to picker j

y_j : 1 if picker j has been employed for any order picking

ot_j : The amount of overtime for picker j

RA_{ij} : RA required by picker j for order i

$$\min_{y,ot} \sum_{j \in J} a \cdot y_j + \sum_{j \in J} p \cdot ot_j \tag{2}$$

subject to

$$\sum_{j \in J} x_{ij} = 1 \qquad \forall i \in I \tag{3}$$

$$\sum_{i\in S_k} t_i \cdot \left(1+RA_{ij}\right)\cdot x_{ij} - ot_j \le t_{\text{limit}} \qquad \forall k\in K, j\in J \tag{4}$$

$$x_{ij} \le y_j \qquad \forall i\in I, j\in J \tag{5}$$

$$x_{ij} \in \{0,1\} \qquad \forall i\in I, j\in J \tag{6}$$

$$y_j \in \{0,1\} \qquad \forall j\in J \tag{7}$$

$$ot_j \ge 0 \qquad \forall j\in J \tag{8}$$

$$RA_{ij} \ge 0 \qquad \forall i\in I, j\in J \tag{9}$$

Eq. (2) presents the objective function, which includes the cost of assignment and overtime for daily demand. Constraint (3) ensures that each order i is strictly assigned to a picker. Constraint (4) calculates the overtime considering the energy expenditure and OP tour time jointly. The RA amount is added to the tour time of the order picker and the OP tour time with RA is $t_i \cdot \left(1+RA_{ij}\right)$. Constraint (5) shows whether picker j is employed. Constraints (6-9) define the type of variables in the model formulation. The mathematical model presented above is not linear due to the product of variables x_{ij} and RA_{ij} in Eq. (4). Thus, Constraint (4) is rewritten in the following formulation:

$$\sum_{i\in S_k} \text{TRA}_{ij} + \sum_{i\in S_k} t_i \cdot x_{ij} - ot_j \le t_{\text{limit}} \qquad \forall k\in K, j\in J \tag{10}$$

where, TRA_{ij} is:

$$\text{TRA}_{ij} = \max\left\{0, t_i \cdot \frac{e_{ij}-e_{\text{limit}}}{e_{\text{limit}}-e_{\text{rest}}} \cdot x_{ij}\right\} \qquad \forall i\in I, j\in J \tag{11}$$

To linearize Eq. (11), the below constraints in Eq. (12-16) are included in the model.

$$\text{TRA}_{ij} \ge 0 \qquad \forall i\in I, j\in J \tag{12}$$

$$\text{TRA}_{ij} \ge t_i \cdot \frac{e_{ij}-e_{\text{limit}}}{e_{\text{limit}}-e_{\text{rest}}} \cdot x_{ij} \qquad \forall i\in I, j\in J \tag{13}$$

$$\text{TRA}_{ij} \le \text{BM} \cdot \left(1-w_{ij}\right) \qquad \forall i\in I, j\in J \tag{14}$$

$$\text{TRA}_{ij} \le t_i \cdot \frac{e_{ij}-e_{\text{limit}}}{e_{\text{limit}}-e_{\text{rest}}} \cdot x_{ij} + \text{BM}\cdot w_{ij} \qquad \forall i\in I, j\in J \tag{15}$$

$$w_{ij} \in \{0,1\} \qquad \forall i\in I, j\in J \tag{16}$$

In Eq. (14-16), BM refers to the big-M, a large number; w_{ij} is a binary variable that arranges the selection of the highest value for TRA_{ij}, 0 or $t_i \cdot \frac{e_{ij}-e_{\text{limit}}}{e_{\text{limit}}-e_{\text{rest}}} \cdot x_{ij}$. The deterministic form of the developed model is Eqs. (2-3), Eqs. (5-10), and Eqs. (12-16). However, because OP tour time t_i and energy consumption e_{ij} are uncertain random variables, the core deterministic model is extended to a two-stage stochastic programming model in Section 4.2.

4.2. Two-stage stochastic model

In the stochastic model, we assumed that OP tour time and associated energy expenditure during picking are uncertain parameters with the known joint distribution. The uncertain parameters are denoted by ξ, $\xi = \left(\tilde{t}, \tilde{e}\right)$, and the tilde mark is used to distinguish uncertain parameters from their deterministic counterparts. The objective of the developed two-stage stochastic program in Eqs. (17-29) is to minimize the total assignment cost and the expected penalized overtime needed to meet the demand. The first stage decision variable y_j, simply Y, shows the assigned workers for order picking. The second stage decision variable is ot_j, simply OT, and shows pickers' overtime hours to meet the demand.

$$\min_y \sum_{j\in J} a \cdot y_j + E\left[Q\left(y,\xi\right)\right] \tag{17}$$

subject to

$$\sum_{j\in J} x_{ij} = 1 \qquad \forall i \in I \tag{18}$$

$$x_{ij} \le y_j \qquad \forall i \in I,\, j \in J \tag{19}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in I,\, j \in J \tag{20}$$

$$y_j \in \{0,1\} \qquad \forall j \in J \tag{21}$$

where

$$Q(y,\xi) = \min_{ot} \sum_{j\in J} p \cdot ot_j \tag{22}$$

subject to

$$ot_j \ge \sum_{i\in S_k} \mathrm{TRA}_{ij} + \sum_{i\in S_k} \tilde{t}_i \cdot x_{ij} - t_{\mathrm{limit}} \qquad \forall j \in J,\, k \in K \tag{23}$$

$$\mathrm{TRA}_{ij} \ge 0 \qquad \forall i \in I,\, j \in J \tag{24}$$

$$\mathrm{TRA}_{ij} \ge \tilde{t}_i \cdot \frac{\tilde{e}_{ij} - e_{\mathrm{limit}}}{e_{\mathrm{limit}} - e_{\mathrm{rest}}} \cdot x_{ij} \qquad \forall i \in I,\, j \in J \tag{25}$$

$$\mathrm{TRA}_{ij} \le \mathrm{BM} \cdot (1 - w_{ij}) \qquad \forall i \in I,\, j \in J \tag{26}$$

$$\mathrm{TRA}_{ij} \le \tilde{t}_i \cdot \frac{\tilde{e}_{ij} - e_{\mathrm{limit}}}{e_{\mathrm{limit}} - e_{\mathrm{rest}}} \cdot x_{ij} + \mathrm{BM} \cdot w_{ij} \qquad \forall i \in I,\, j \in J \tag{27}$$

$$w_{ij} \in \{0,1\} \qquad \forall i \in I,\, j \in J \tag{28}$$

$$ot_j \ge 0 \qquad \forall j \in J \tag{29}$$

Eq. (17) presents the objective function of the two-stage stochastic programming model, which minimizes the first-stage cost and expected second-stage cost under a set of possible scenarios. The first term in the objective function is the first-stage cost, which refers to the total assignment cost of pickers for OP. The second term in the objective function is the expected total cost of penalized overtime associated with exceeding the regular working hours, i.e., the expected value of the recourse function. The expected value of the recourse function for a given assignment $\hat{x}_{ij}$ is

$$E\left[\sum_{j\in J} p \left(\sum_{i\in S_k} \mathrm{TRA}_{ij} + \sum_{i\in S_k} \tilde{t}_i \cdot \hat{x}_{ij} - t_{\mathrm{limit}}\right)^{+}\right] = \sum_{j\in J} p\, E\left[\left(\sum_{i\in S_k} \mathrm{TRA}_{ij} + \sum_{i\in S_k} \tilde{t}_i \cdot \hat{x}_{ij} - t_{\mathrm{limit}}\right)^{+}\right] \tag{30}$$

where $E\left[\left(\sum_{i\in S_k} \mathrm{TRA}_{ij} + \sum_{i\in S_k} \tilde{t}_i \cdot \hat{x}_{ij} - t_{\mathrm{limit}}\right)^{+}\right]$ is the expected overtime for picker j.

Constraints (17) – (21) present the first stage model, in which the orders are assigned to the pickers, and constraints (22) – (29) denote the second stage model that calculates the penalized overtime to meet the demand.

5. Solution method

There are two potential difficulties in solving the two-stage stochastic model presented in Section 4.2. The first difficulty is the computation of the objective function for a given set of pickers, which requires the calculation of the $E[Q(y,\xi)]$ in Eq (17). When the uncertain parameter, such as OP tour time and energy expenditure in our problem, has continuous distribution, the exact calculation of this expected value involves the computation of multiple integrals (Santoso et al., 2005). The second obstacle is the optimization of the expected overtime cost $E[Q(y,\xi)]$ due to not having the closed analytical form of the $E[Q(y,\xi)]$. To overcome these issues, the Sample Average Approximation (SAA) algorithm is introduced by Kleywegt, Shapiro, & Homem-de-Mello (2002). SAA is a Monte Carlo-based optimization method for solving stochastic optimization problems. The overall idea behind the SAA is approximating the expected objective function through a sample average obtained from a random sample. The SAA searches the solution space iteratively, increasing the set of scenarios until ε – optimal solution is found. In the SAA algorithm, random sample $\xi^1,\ldots,\xi^N$ of N scenarios of the OP tour time and energy expenditure are generated according to the prior known probability distributions. Then, expectation in the objective function $E[Q(y,\xi)]$ is approximated by the SAA function, $\sum_{n=1}^{N} Q(y,\xi^n)/N$. Finally, the true problem in Eq. (17) – (21) is approximately calculated by the SAA problem in Eq. (31), where $a^T y$ resents the total assignment costs and $\sum_{n=1}^{N} Q\left(y,\xi^n\right)\big/N$ shows the expected overtime costs.

$$\hat{z}_N = \min_y \; a^T y + \frac{1}{N}\sum\nolimits_{n=1}^{N} Q\left(y,\xi^n\right) \tag{31}$$

As sample size N increases, the optimal solution of the SAA problem $\hat{y}$ and its objective function $\hat{z}_N$ converges to the optimal optimal solution y^* and value z^* of the true problem with probability one (i.e., asymptotic convergence). The steps of the SAA algorithm are presented below:

Step 1: Generate M independent samples each of size N and solve the SAA problem in Eq. (31). For $j = 1,...,M$, $\hat{z}_N^m$ and $\hat{y}_N^m$ denote the corresponding optimal objective function value and optimal solutions.

Step 2: Compute $\overline{z}_M$ and $\sigma^2_{z_M}$ as follows as in Eqs. (32-33), respectively:

$$\overline{z}_M = \frac{1}{M}\sum_{m=1}^{M} \hat{z}_N^m \tag{32}$$

$$\sigma^2_{z_M} = \frac{1}{\left(M-1\right)M}\sum_{m=1}^{M}\left(\hat{z}_N^m - \overline{z}_M\right)^2 \tag{33}$$

$\overline{z}_M$ is an unbiased estimator of $E\left[\overline{z}_M\right]$, and $E\left[\overline{z}_M\right] \le z^*$ (Mak et al., 1999; Santoso et al., 2005). Therefore, $\overline{z}_M$ produces a lower bound for the optimal value of the true stochastic problem, z^*.

Step 3: Find the $\hat{y}^*$, optimal solution among m solutions that provides the minimum objective value as in Eq. (34),

$$\hat{y}^* \in \arg\min\left\{\hat{z}_N\left(\hat{y}\right) : \hat{y} \in \left\{\hat{y}^1, \hat{y}^2, ..., \hat{y}^m\right\}\right\} \tag{34}$$

Then, generate another sample size of N', independent from the previous sample N. Note that N' is much larger than the sample size of SAA problems. Next, fixing the optimal solution $\hat{y}^*$, estimate the true objective function $z^{N'}\left(\hat{y}^*\right)$. This step includes solving N' second-stage problems as in Eq. (35).

$$z^{N'}(\hat{y}^*) = a^T\hat{y}^* + \frac{1}{N'}\sum\nolimits_{n=1}^{N'} Q\left(\hat{y}^*,\xi^n\right) \tag{35}$$

$z^{N'}(\hat{y}^*)$ is unbiased estimator of $a^T\hat{y}^* + E\left[Q\left(\hat{y}^*,\xi^n\right)\right]$. For any feasible $\hat{y}^*$, $z^{N'}(\hat{y}^*) \ge z^*$ (Mak et al., 1999; Santoso et al., 2005). Thus, $z^{N'}(\hat{y}^*)$ produces an upper bound for the optimal value. The variance of the estimate is:

$$\sigma^2_{z^{N'}(\hat{y}^*)} = \frac{1}{\left(N'-1\right)N'}\sum_{n=1}^{N'}\left(a^T\hat{y}^* + Q\left(\hat{y}^*,\xi^n\right) - z^{N'}(\hat{y}^*)\right)^2 \tag{36}$$

Step 4: Compute the optimality gap through lower and upper bound estimates as follows:

$$gap\left(\hat{y}^*\right) = z^{N'}(\hat{y}^*) - \overline{z}_M \tag{37}$$

The estimated variance of the optimality gap is

$$\sigma^2_{gap} = \sigma^2_{z^{N'}(\hat{y}^*)} - \sigma^2_{z_M} \tag{38}$$

Step 5: If the optimality gap is less than ε, stop the algorithm and choose $\hat{y}^*$ as optimal solution; otherwise, increase M, N, N' and repeat steps (1-4).

6. Computational experiments

In this section, first, common data used in the numerical studies are presented in Section 6.1. Then, in Section 6.2, the capability of the proposed model is tested by solving two benchmark problems. However, it is important to mention that the primary objective of this study is to discover the impact of pickers' weight and energy consumption on the picker assignment problem for warehouses. In this regard, this research does not center on the computational capability of the mathematical model. Instead, it focuses on the impact of pickers' weight on the number of required pickers and OP costs. Therefore, to evaluate the benefits achieved by applying the proposed model, Section 6.3 is designed to answer RQ1, while Section 6.4 is constructed to investigate RQ2. Last, Section 6.5 presents the value of the stochastic solution. All the numerical experiments are conducted on a PC with Intel Core i7/2.5GHz/8GB RAM using GAMS 23.3 with a CPLEX solver.

6.1. Data

Data used in the model about the warehouse design parameters and OP tour time are based on a former simulation study conducted by Al-Araidah et al. (2021). In that study, energy expenditure levels are calculated by Garg et al. (1978), considering the design and pick-up time of the orders. Table 2 presents the list of all the parameters used in the study with the collected resources.

Table 2
Model parameters

Parameters	Values
Cost related parameters	
a	116.64$/day [14.58$/hr × 8hr] (Bureau of Labor Statistics 2021)
p	0.365$/min [× 1.5 assignment cost]
Picker related parameters	
Walking speed	1.3m/s
e_{limit}	4 Kcal/min Kcal/min (Morelli 2001)
e_{rest}	1.86 Kcal/min (Finco et al. 2020)
Warehouse related parameters	
Aisle width	1m (Al-Araidah et al. 2021)
Number of aisles	3 (Al-Araidah et al. 2021)
Compartment width	0.5m (Al-Araidah et al. 2021)
Shelf height	0.3m (Al-Araidah et al. 2021)
Rack depth	0.5m (Al-Araidah et al. 2021)
Bench height	0.81m (Al-Araidah et al. 2021)
Storage locations	720 (Al-Araidah et al. 2021)
Order related parameters	
Item weight in the order	1kg (Al-Araidah et al. 2021)
Basket weight	0.68kg (Al-Araidah et al. 2021)

The energy expenditure (e_{ij}) and the OP tour time (t_i) are approximated to follow a normal distribution with a mean of μe_{ij} and μt_i; and variance of σe_{ij}^2 and σt_i^2, respectively, based on simulation of 10,000 orders (Al-Araidah et al., 2021) as presented in Table 3.

Table 3
OP time and energy expenditure of the pickers depending on weight under the walking speed of 1.3 m/s

Order configuration	Time in min (No allowance)		Energy expenditure (Kcal/min)							
			70kg		80kg		90kg		100kg	
	μt_i	σt_i^2	μe_{ij}	σe_{ij}^2	μe_{ij}	σe_{ij}^2	μe_{ij}	σe_{ij}^2	μe_{ij}	σe_{ij}^2
1-item	0.381	0.014	3.764	0.042	4.232	0.052	4.700	0.063	5.168	0.075
2-items	0.630	0.015	3.734	0.023	4.197	0.028	4.660	0.034	5.123	0.041
3-items	0.873	0.022	3.743	0.017	4.202	0.022	4.662	0.027	5.122	0.032
4-items	1.119	0.028	3.768	0.013	4.226	0.017	4.685	0.020	5.143	0.025
5-items	1.368	0.035	3.804	0.012	4.261	0.015	4.719	0.018	5.176	0.021

In all numerical experiments, the number of orders and item counts in each order $K = \{1,...,5\}$ are randomly generated to derive insights about the picker's weight. The SAA parameters used in the numerical studies are $M = 5,\ N = 20,\ N' = 50$.

6.2. Computational analysis

We tailored some well-known data sets for our problem to illustrate the model's capability to find a solution. Because our problem is related to GAP and OP allocation, we select two different datasets (Spoerl & Wood, 2003; Henn, 2015) to cover both aspects of the problem. However, due to the incorporation of warehouse and energy expenditure-related parameters and constraints in our model, it is impossible to compare their models and ours based on the objective function. Therefore, the solution time metric is used for the comparison. Table 4 presents the data instances and compares the solution times of Spoerl & Wood (2003) and our model. The modifications in our data set are as follows: (i) the number of trucks and operators in the original dataset is replaced by the number of pickers and orders, (ii) the number of items in the orders is assumed to be uniformly distributed between 1 and 5 and, (iii) all pickers assumed to weigh 70kg.

Table 4
Solution time for the data instances adopted from (Spoerl & Wood, 2003)

Data instances	Pickers	Orders	Solution Time (CPU Seconds)			
			Deterministic	Stochastic		Our solution
			EGAP	PMVM	GMVM	
XSLONGD	6	21	0.3	0.3	0.2	2.4
XSLONGN	8	22	0.3	0.3	0.2	2.5
XSBOSTD	15	50	0.5	1	1.6	4.5
XSBOSTN	17	56	1.3	0.8	1.2	4.9
XSDLWRN	11	48	0.3	0.3	0.8	3.6
XSDLWRD	19	70	0.4	1.4	21.5	5.9
XSLOSAD	34	151	44.8	9.8	403.6	17.1
XSLOSAN	35	147	19.9	110.3	164.3	17.2

* PMVM: proportional mean-variance model, GMVM: general mean-variance model – stochastic approaches used in their study

Table 4 shows that our model can solve all the instances in less than 17.2 seconds. Another comparison was performed over the data set used by Henn (2015), which deals with the picker assignment and scheduling problem. In Henn (2015), two different order quantities, 100 and 200, were assigned to a number of 2, 3, 5, and 8 pickers. The objective was to minimize the total due date tardiness. The following assumptions were needed for the comparison: (i) because our problem does not deal with order scheduling, we modified our model not to allow overtime; (ii) we assumed that each batch consisted of one order; (iii) the number of items in the orders are uniformly distributed between 1 and 5 and, (iv) all pickers were assumed to weigh 70kg. Our model was able to solve eight instances [2 (number of orders 100 and 200) × 4 (number of pickers 2, 3, 5, and 8)] in less than 7 CPU seconds.

Solution time depends on many problem parameters and constraints. For example, the sensitivity of the solution time regarding overtime cost was mentioned in (Spoerl & Wood, 2003). In this manner, rather than making a fair comparison between the benchmark data sets and our model, the results provide a base to understand that our model can solve the test instances in a reasonable time. All the numerical experiments in Sections 6.3-6.5 were successfully solved in less than 1.6 hours.

6.3. Impact of weight on total cost and number of order pickers

Weight is a significant factor used in the calculations of energy expenditure. In this numerical experiment, the impact of OP's weight on the total number of pickers and the total OP costs was investigated. Therefore, a typical daily demand of 3360 orders consisting of 1264, 760, 552, 432, and 352 orders for each order configuration (1-item to 5-items), respectively, was selected from one of (Al-Araidah et al., 2021)'s experiments. Ten different sets of scenarios in which the weight of the picker changes from 50kg to 100kg are generated. In these experiments, we assumed that all the pickers weigh the same, changing respect to scenarios. Then, using the energy expenditure of the various picker's weights (Kcal/min) from the simulation model (Al-Araidah et al., 2021), the two-stage stochastic programming model was solved to decide the number of pickers. Fig. 1 demonstrates the number of pickers and total OP costs for ten scenarios. As seen in Fig. 1, there was no change in the number of pickers and the total OP cost when the picker was between 50kg and 74kg. However, the total OP cost increased as weight exceeded 74kg, especially above 80kg. On the other hand, the number of workers remained the same until 80kg and suddenly increased to seven and eight for 90kg and 100kg, respectively.

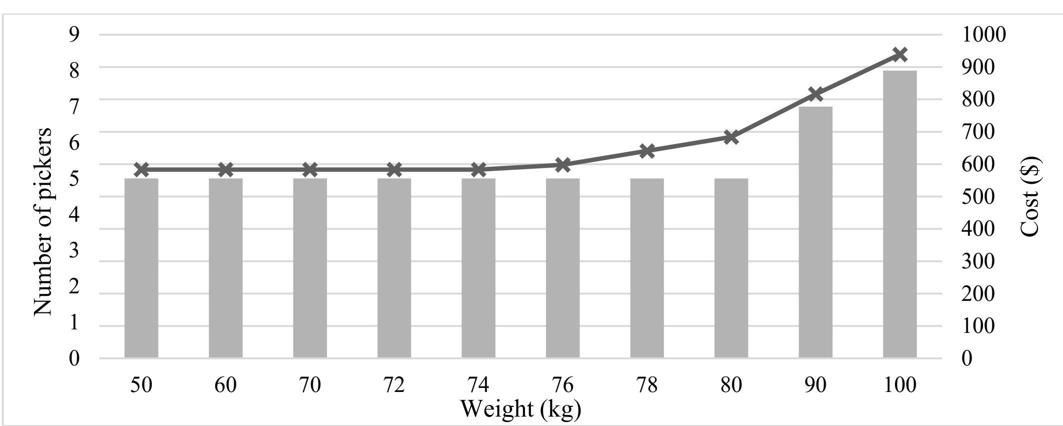


Fig. 1. Variation in total cost and number of pickers concerning pickers' weight for a daily demand

According to the weight percentile calculator for women 18 years and older in the United States (PK, 2023a), the median weight is 74kg. In our numerical experiment, a weight of 74kg constitutes a threshold for OP costs, implying that a rise occurs in costs when the picker's weight exceeds 74kg. Similarly, another weight percentile by age calculator for adult women in the United States (PK, 2023b) computes that the median weight for the age interval of 35-39 is almost 78kg. This numerical study illustrates that the number of pickers required to fulfill the same order quantity increases when the picker's weight exceeds

80kg. Using the two statistics (PK, 2023a; 2023b) and the results of the numerical study, an insight for warehouse managers is that pickers below 80kg provide a better match to fulfill the demand with fewer pickers and costs.

6.4. Impact of weight on order-picker match

This numerical experiment investigates how a better fit between order configuration and pickers with different weights can be achieved. We aim to reveal which order configuration can be allocated by what weight picker so that full benefit from the human resource is gained while considering their energy expenditure. For a daily demand of 4500 orders, 900 from each order configuration, we generate 11 scenarios (S1-S11) in which the weights of pickers range between 70kg and 100kg. In these scenarios, weight is considered in three segments: low-weight, medium-weight, and high-weight. Pickers weighing 70kg-80kg dominate in the low-weight segment, whereas 90kg-100kg pickers dominate in the high-weight segment. The medium-weight segment is between the low- and high-weight segments, showing that almost the same number of pickers are included between 70kg and 100kg. All 11 scenarios with three weight segments are presented in Table 5. In Table 5, the first four scenarios (S1-S4) belong to the low-weight segment; the following three scenarios (S5-S7) belong to the medium-weight segment; and the last four scenarios (S8-S11) belong to the high-weight segment. The first scenario (S1) includes five pickers weighing 70kg and four weighing 80kg. The weight distribution of the pickers for the rest of the scenarios can be read similarly.

Table 5
The weight distribution of pickers

Weight	Number of pickers										
	Low-weight segment				Medium-weight segment			High-weight segment			
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
70kg	5	4	6	1	3	0	0	1	1	0	0
80kg	4	5	1	6	2	5	4	1	1	0	0
90kg	0	0	1	1	2	4	5	6	1	5	4
100kg	0	0	1	1	2	0	0	1	6	4	5
Avg. weight(kg)	74.44	75.56	76.67	82.22	83.33	84.44	85.56	87.78	93.33	94.44	95.56

The two-stage stochastic programming model for each scenario is solved, and the results for each weight segment are presented in Tables 6-8. For instance, in Scenario 1 in Table 6, only eight workers out of nine are allocated, and no order is assigned to the last picker weighing 80kg. The first picker weighing 70kg was assigned a total of 557 orders, which are 133, 51, 44, 145, and 184 for each configuration ranging from 1-item to 5-item.

Table 6
The number of orders assigned to pickers in the low-weight segment

	Order configuration	70kg	70kg	70kg	70kg	70kg	80kg	80kg	80kg	80kg
Scenario 1	1-item	133	139	128	130	122	87	78	83	-
	2-items	51	53	45	51	52	210	226	212	-
	3-items	44	49	64	49	49	211	219	215	-
	4-items	145	137	136	121	140	79	67	75	-
	5-items	184	174	201	176	164	1	-	-	-
	Total	*557*	*552*	*574*	*527*	*527*	*588*	*590*	*585*	*0*
	Order configuration	**70kg**	**70kg**	**70kg**	**70kg**	**80kg**	**80kg**	**80kg**	**80kg**	**80kg**
Scenario 2	1-item	116	125	128	133	100	105	94	99	-
	2-items	28	23	25	30	199	177	208	210	-
	3-items	34	39	42	34	195	181	189	186	-
	4-items	135	115	147	121	92	107	90	93	-
	5-items	210	220	223	235	1	6	4	1	-
	Total	*523*	*522*	*565*	*553*	*587*	*576*	*585*	*589*	*0*
	Order configuration	**70kg**	**70kg**	**70kg**	**70kg**	**70kg**	**70kg**	**80kg**	**90kg**	**100kg**
Scenario 3	1-item	126	129	124	134	122	154	76	35	-
	2-items	78	62	77	76	76	86	277	168	-
	3-items	88	81	86	89	69	82	205	200	-
	4-items	141	152	108	128	141	127	50	53	-
	5-items	149	136	160	133	152	166	4	-	-
	Total	*582*	*560*	*555*	*560*	*560*	*615*	*612*	*456*	*0*
	Order configuration	**70kg**	**80kg**	**80kg**	**80kg**	**80kg**	**80kg**	**80kg**	**90kg**	**100kg**
Scenario 4	1-item	129	117	100	100	118	123	121	92	-
	2-items	12	154	133	135	140	127	126	73	-
	3-items	12	146	144	139	125	125	127	82	-
	4-items	85	111	126	120	112	130	116	100	-
	5-items	583	32	35	42	50	40	51	67	-
	Total	*821*	*560*	*538*	*536*	*545*	*545*	*541*	*414*	*0*

Going in depth in this analysis to reveal what weight pickers are prevalently assigned to which order configuration, the percentages of assignments are calculated using Table 6 and are presented in Figs. 2(a)-(d). For instance, in Fig. 2(a), approximately 20% of the total orders assigned to 70 kg weighing pickers consist of 1-item orders, while almost 65% of their assignments include 4- (≅25%) and 5-items (≅%40).

These percentages in Figs. 2(a)-(d) show that orders containing 4- and 5- items are predominantly assigned to pickers weighing 70kg, while orders including 2- and 3-items are primarily assigned to 80kg weight pickers. Basically, the average amount of energy expenditure (Kcal/min) increases as the number of items in the order increases. This consumption is higher for heavier pickers. For instance, while the energy expenditure of a 70kg weight picker for a 5-items order is 3.804 Kcal/min, it is 4.261 Kcal/min on average for an 80kg picker. Additionally, because the energy expenditure of an 80kg picker is above 4Kcal/min (MAEE), she is given RA time, which increases the total OP time and costs. Therefore, for a group of pickers weighing between 70kg to 90kg, 4- and 5-item orders are assigned to the lower-weight pickers (70kg). On the other hand, relatively heavier pickers (80kg and 90kg) are assigned to orders consisting of 2- and 3- items.

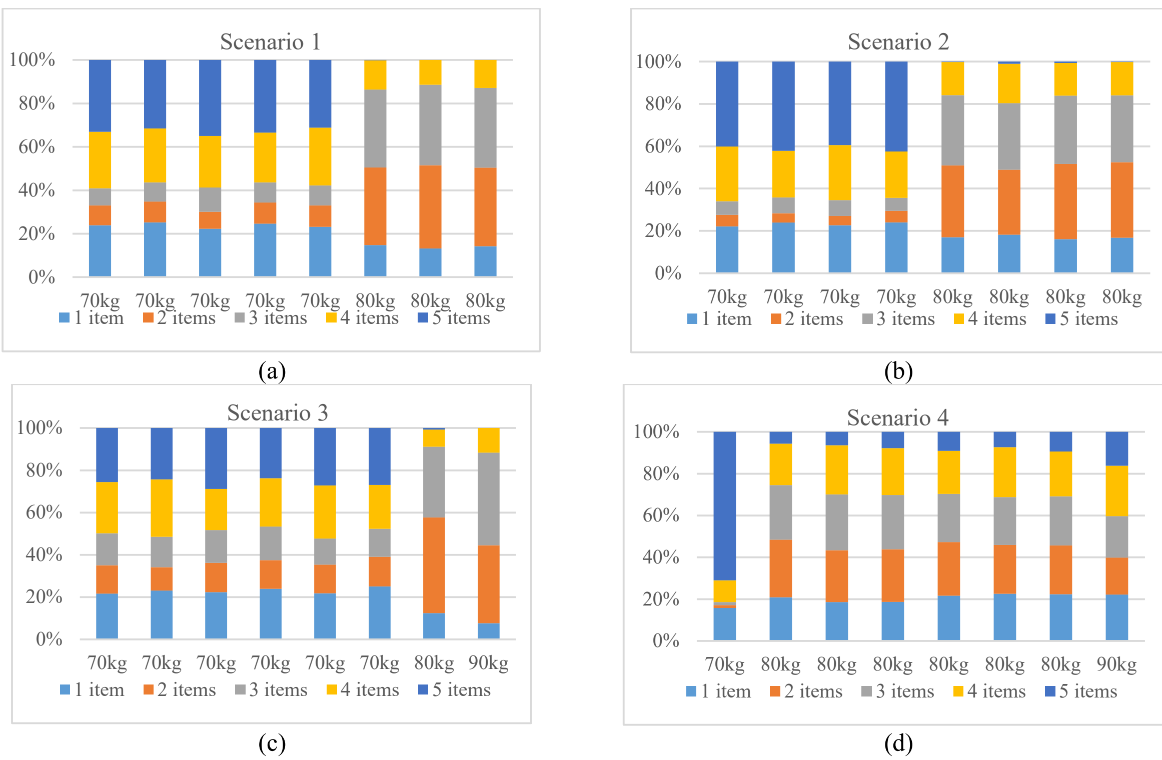


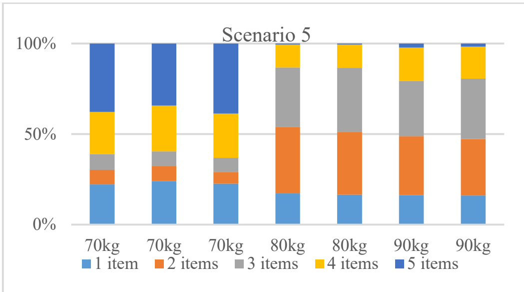
Fig. 2. Percentage of order configuration allocated to pickers in the low-weight segment for scenarios S1-S4, (a)-(d), respectively

Table 7 illustrates the assignment results for the medium-weight segment. The percentages of items assigned to pickers for the medium-weight segment are presented in Figures 3(a)-(c).

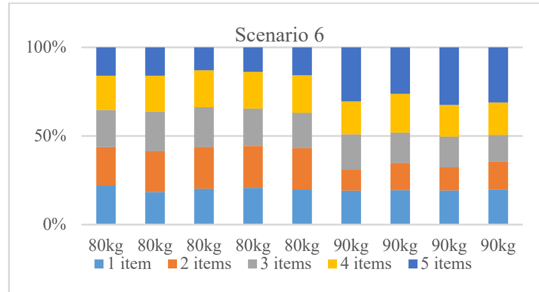
Table 7
The number of orders assigned to pickers in the medium-weight segment

	Order configuration	**70kg**	**70kg**	**70kg**	**80kg**	**80kg**	**90kg**	**90kg**	**100kg**	**100kg**
Scenario 5	1-item	174	197	177	103	98	76	75	-	-
	2-items	63	67	49	220	205	151	145	-	-
	3-items	68	68	62	196	209	142	155	-	-
	4-items	182	207	191	76	76	86	82	-	-
	5-items	295	280	301	3	3	10	8	-	-
	Total	*782*	*819*	*780*	*598*	*591*	*465*	*465*	*0*	*0*
Scenario 6	**Order configuration**	**80kg**	**80kg**	**80kg**	**80kg**	**80kg**	**90kg**	**90kg**	**90kg**	**90kg**
	1-item	130	115	120	126	115	72	75	72	75
	2-items	126	144	140	144	134	44	59	49	60
	3-items	122	140	133	128	115	75	66	64	57
	4-items	113	126	123	126	122	70	84	67	69
	5-items	94	100	77	84	91	114	101	121	118
	Total	*585*	*625*	*593*	*608*	*577*	*375*	*385*	*373*	*379*
Scenario 7	**Order configuration**	**80kg**	**80kg**	**80kg**	**80kg**	**90kg**	**90kg**	**90kg**	**90kg**	**90kg**
	1-item	130	129	114	138	73	81	70	82	83
	2-items	153	155	135	151	72	60	57	52	65
	3-items	137	153	155	147	59	52	71	52	74
	4-items	132	114	116	141	83	82	73	80	79
	5-items	95	104	85	88	101	109	109	114	95
	Total	*647*	*655*	*605*	*665*	*388*	*384*	*380*	*380*	*396*

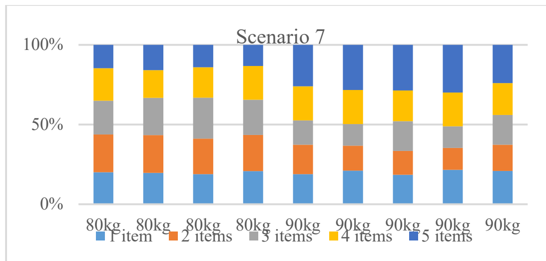
Fig. 3(a) shows that 70 kg weighing pickers are mostly allocated for 5-item orders. However, pickers are assigned orders from all configurations almost equally when the individuals weighing 80-90 kg in Figs. 3(b)-(c).



(a)



(b)



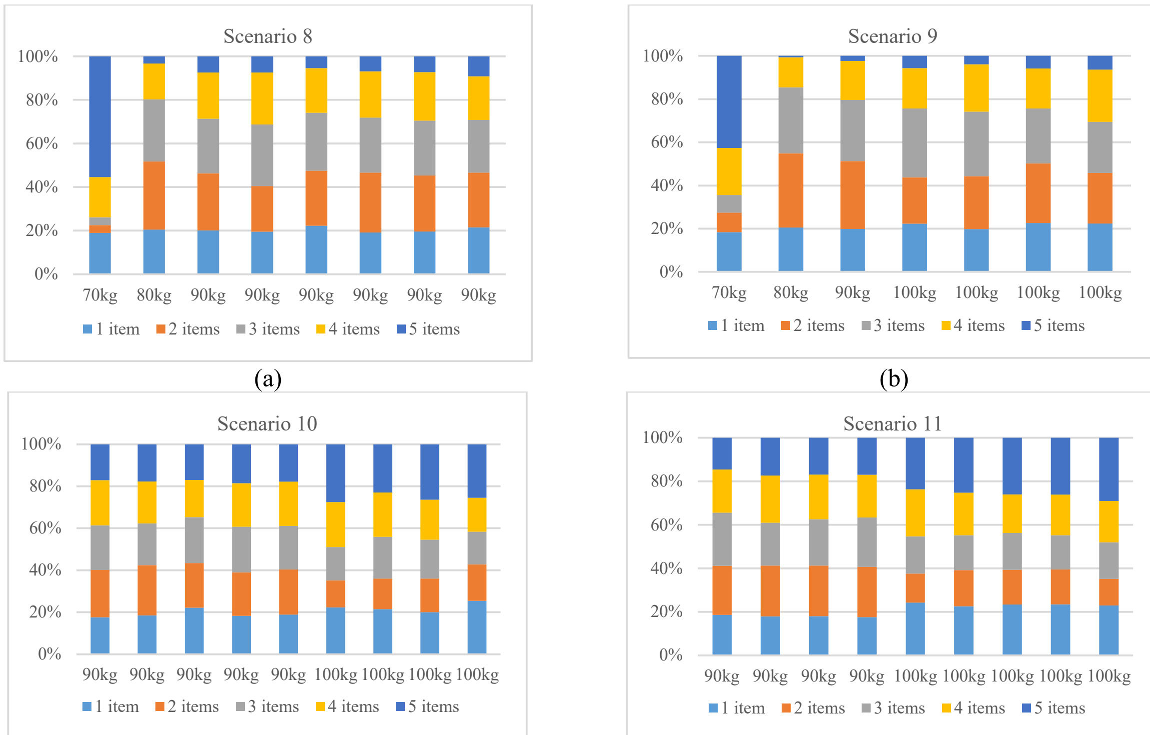
(c)

Fig. 3. Percentage of order configuration allocated to pickers in the medium-weight segment for scenarios S5-S7, (a)-(c), respectively

Table 8 illustrates the distribution of total orders assigned to the high-weight segment. There is no balanced distribution across pickers in the high-weight segment, unlike in the low-weight segment. For example, in Scenario 8, a total of 1240 orders are assigned to a 70kg weighting picker, while an average of 446.5 orders are assigned to a 90kg picker, and no order is assigned to a 100kg picker.

Table 8
The number of orders assigned to pickers in the high-weight segment

	Order configuration	**70kg**	**80kg**	**90kg**	**90kg**	**90kg**	**90kg**	**90kg**	**90kg**	**100kg**
Scenario 8	1-item	235	119	90	85	102	86	87	96	-
	2-items	45	182	117	91	116	123	114	112	-
	3-items	45	165	112	123	122	113	112	108	-
	4-items	228	96	95	104	94	95	99	89	-
	5-items	687	19	33	32	25	31	32	41	-
	Total	*1240*	*581*	*447*	*435*	*459*	*448*	*444*	*446*	*0*
	Order configuration	**70kg**	**80kg**	**90kg**	**100kg**	**100kg**	**100kg**	**100kg**	**100kg**	**100kg**
Scenario 9	1-item	346	124	94	86	76	89	85	-	-
	2-items	169	207	149	83	94	109	89	-	-
	3-items	154	184	134	123	115	100	90	-	-
	4-items	409	84	86	72	84	73	92	-	-
	5-items	801	4	11	22	15	23	24	-	-
	Total	*1879*	*603*	*474*	*386*	*384*	*394*	*380*	*0*	*0*
	Order configuration	**90kg**	**90kg**	**90kg**	**90kg**	**90kg**	**100kg**	**100kg**	**100kg**	**100kg**
Scenario 10	1-item	116	119	130	119	117	73	72	66	88
	2-items	149	154	125	135	133	42	49	53	60
	3-items	140	128	128	141	129	52	67	61	54
	4-items	142	128	104	135	131	70	71	63	56
	5-items	113	114	100	121	110	90	77	87	88
	Total	*660*	*643*	*587*	*651*	*620*	*327*	*336*	*330*	*346*
	Order configuration	**90kg**	**90kg**	**90kg**	**90kg**	**100kg**	**100kg**	**100kg**	**100kg**	**100kg**
Scenario 11	1-item	138	127	122	122	82	76	79	79	75
	2-items	167	166	158	160	45	56	54	54	40
	3-items	181	140	144	158	58	54	57	53	55
	4-items	147	154	139	136	73	66	60	63	62
	5-items	108	123	115	118	80	85	88	88	95
	Total	*741*	*710*	*678*	*694*	*338*	*337*	*338*	*337*	*327*



(a) (b)

(c) (d)

Fig. 4. Percentage of order configuration allocated to pickers in the high-weight segment for scenarios S8-S11, (a)-(d), respectively

Figs. 4 (a)-(d) present the percentage of order configuration allocated to pickers in the high-weight segment. 5-item orders are predominantly assigned to a 70kg picker, as seen in Fig. 4 (a) and Fig. 4 (b), whereas heavier pickers are mainly responsible for the 2- and 3-item orders. With no low-weight picker (70kg), almost similar assignment ratios per order configuration are observed for pickers.

6.5. Value of Stochastic Solution

In this part, we considered several different values of $N = \{2, 5, 10, 20, 40, 50\}$ to investigate the impact of randomness on solution quality. For each OP time and energy expenditure scenario, five independent samples $(M = 5)$ are produced, and the true objective function $z^{N'}(\hat{y}^*)$ is estimated with $N' = 50$. Table 9 presents the optimality gap and the variance of the optimality gap for each configuration. In Table 9, the standard deviation and the optimality gap decreases as the number of scenarios increases. Additionally, a modest sample size $(N = 5)$ can provide a small optimality gap (e.g., \$1.44), which verifies that the SAA parameters used in the numerical study achieve good precision in solution derivation.

Table 9
Estimation of the true objective function

N	Optimality gap	Variance of the optimality gap
2	2.636	0.004
5	1.440	0.003
10	0.838	0.001
20	0.416	0.001
40	0.095	0.002
50	0.011	0.002

Finally, we compare objective functions of stochastic problems and their deterministic counterparts to present the benefit of developing a stochastic solution, which is called the value of stochastic solution (VSS). The idea behind VSS is to show the advantage of spending time by developing a stochastic programming model instead of using its deterministic counterpart, which is based on the mean value of uncertain parameters. The deterministic counterpart of the problem is generated by replacing all uncertain parameters with their mean values and is called an expected value problem (EV), which can be formalized as follows: $EV = \min_{x \in X} z\left(x, \bar{\xi}\right)$ where $\bar{\xi}$ represents the expected value of the uncertain OP tour time and energy expenditure in our model. Therefore, instead of using uncertain OP tour times that depend on item counts in the order, we used the mean OP tour time (0.87 min/order), calculated by taking the overall average of OP tour time across orders. Similarly, for the energy expenditure, we used the mean energy expenditure of a 70kg female (3.76 Kcal/min) for picking each order in the EV problem. The solution of the EV problem, optimal picker assignment, is represented by $\bar{x}\left(\bar{\xi}\right)$. Using the solution of the EV problem, $\bar{x}\left(\bar{\xi}\right)$, the expected total cost EEV is calculated under different OP tour time and energy expenditure scenarios as follows $EEV = E\left[z\left(\bar{x}\left(\bar{\xi}\right),\xi\right)\right]$. Last, the difference between the total cost of deterministic and stochastic models is calculated, $VSS = EEV - RP$. In the formulation, RP refers to the total cost of a stochastic program with fixed recourse (Birge & Louveaux, (2011).

Table 10 presents the EEV, RP, VSS and the $\%VSS$ values for each scenario in Section 6.4. As seen in Table 10, the stochastic model always produces better solutions than their deterministic counterparts. VSS values range from 7.15$ to 66.58$, equivalent to an average improvement of 3.55% for EEV from RP in daily OP costs.

Table 10
Value of stochastic solution

Scenario	*EEV*	*RP*	*VSS*	%*VSS*
S1	1026.11	1007.55	18.56	1.84
S2	1045.08	1026.10	18.98	1.85
S3	1084.98	1018.40	66.58	6.54
S4	1160.38	1112.78	47.60	4.28
S5	1198.67	1142.89	55.78	4.88
S6	1254.58	1195.12	59.46	4.97
S7	1286.44	1226.66	59.78	4.87
S8	1274.40	1254.72	19.68	1.57
S9	1353.53	1346.38	7.15	0.53
S10	1587.38	1527.92	59.45	3.89
S11	1614.50	1554.83	59.67	3.84
	Average		42.97	3.55

7. Conclusion

This paper investigates the impact of the picker's weight on OP fatigue. Despite the existing literature that considers fatigue effects (e.g., Abdous et al., 2022), this paper proposes a new approach to include fatigue and RA in assigning pickers to orders according to the pickers' weight and item counts in the order. Additionally, the proposed approach is inclusive to cover uncertainty associated with OP tour time and individual differences regarding pickers' weight. We propose a two-stage stochastic programming model that aims to minimize total assignment and overtime costs for OP while avoiding overwhelming energy expenditure by introducing RA. The first stage of the model decides the optimal number of pickers. The second stage allocates orders to pickers based on their energy expenditure concerning their weight. The results highlight that the proposed method outperforms deterministic approaches, with an average of 3.55% reduction in total OP costs. Because fatigue is significantly affected by the weight of pickers, we designed several scenarios to evaluate how the required number of pickers and the match of order-picker assignment are impacted by weight.

Given the scenarios designed, the RQ1 can be answered as follows. Case study results in Section 6.3 demonstrated that the picker's weight impacts the number of required pickers and OP costs. Because the energy expenditure for the same activity is higher for the heavy picker on average, either more pickers were needed or more overtime occurred as additional break time was given to compensate for fatigue effects. The numerical study revealed 80kg as a threshold for the required number of pickers; thus, more pickers are needed to fulfill the exact demand with pickers above 80kg. Given that the median weight for the age interval of 35-39 is 78kg (PK, 2023b), warehouse managers can use the threshold for ideal human resources for OP.

In response to RQ2, the ideal match between pickers and the orders was captured in Section 6.4. For heavy workers, when the item count is four or more, the average energy expenditure increases with less variance, resulting in higher energy expenditure for heavy pickers. In this regard, the numerical study in Section 6.4 demonstrated that low-weight pickers (70kg) were dominantly (approximately 65%) utilized to fulfill the demand of 4- and 5-item orders and secondarily to 1-item orders (around 20%). Similarly, heavier pickers (80kg or above) were assigned to orders of 2- and 3- items. Additionally, the benefit of developing a stochastic model over a deterministic one resulted in an average reduction of 3.55% in OP costs.

One limitation of the proposed solution approach is the lack of fatigue accumulation in fatigue formulation. Several studies show that *fatigue* is defined as a linear function of time, e.g., Jaber and Neumann (2010) or exponential (e.g., Jaber, Givi, & Neumann (2013). In this manner, the fatigue of pickers considering the shifts can be recalculated considering fatigue accumulation with deploying dynamic approaches, such as dynamic programming. Additionally, factors that cause variation in fatigue accumulation can be considered. Therefore, similar to the RA approach, flexible breaks that the number and duration vary depending on human factors can be provided to pickers.

Age is the other factor that has an impact on energy expenditure. The proposed model can be extended to incorporate weight and age as responsible factors for the OP assignment problem. As another extension, developed sensor technology can be deployed to calculate the energy expenditure of the picker in real time and use the data for the assignment. This study solves the problem under the assumption of given demand and the distribution of the energy expenditure and the OP tour time. However, real-time energy expenditure and uncertainty in demand can be considered in a future study. This way, an extension of the model can assist us in comparing and verifying if our findings still imply.

Data availability statement

The data and materials of this study are available from the corresponding author, upon reasonable request.

Disclosure statement

The authors report there are no competing interests to declare.

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