IMPROVING ORDER PICKING LABOR UTILIZATION IN A MANUFACTURING WAREHOUSE USING A HYBRID SIMULATION–OPTIMIZATION APPROACH

P. Sukjumrat[1], N. Sirivongpaisal[1,2*], S. Suwatcharachaitiwong[1,2] and N. Khunjun[2]

[1]Faculty of Engineering, Prince of Songkla University, Hatyai Campus, Songkhla, Thailand.

[2]Smart Industry Research Center, Department of Industrial and Manufacturing Engineering, Prince of Songkla University, Hatyai Campus, Songkhla, Thailand.

*Corresponding Author's Email: nikorn.s@psu.ac.th

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ABSTRACT: Labour utilization is a critical indicator in labour-intensive order picking systems, where excessive walking and non-value-added activities reduce operational efficiency. While prior studies apply simulation or optimization techniques, few systematically integrate experimental design with multi-algorithm benchmarking to evaluate interaction effects on labour utilization. This study proposes a hybrid framework combining discrete-event simulation, Design of Experiments (DOE), and four metaheuristic algorithms—Hill Climbing, Tabu Search, Simulated Annealing, and Particle Swarm Optimization—to analyze the effects of order size, collecting point location, and picking sequence on labour utilization. Both main and interaction effects are examined under identical warehouse conditions. Results show that all three factors significantly affect labour utilization, with notable two-way and three-way interactions. The optimal configuration—middle collecting point with PSO-based routing—improves labour utilization from approximately 55% to 77%. The study's novelty lies in its interaction-aware benchmarking framework, which integrates simulation, factorial DOE, and comparative metaheuristic evaluation within a real warehouse setting. The findings provide practical guidance for improving labour efficiency without major capital investment.

KEYWORDS: *Computer Simulation; Experimental Design; Metaheuristics; Order Picking Process; Labour Utilization*

1.0 INTRODUCTION

Order picking is widely recognized as one of the most labour-intensive and costly activities in manual warehousing systems, accounting for a substantial proportion of total warehouse operating expenses. It significantly influences customer satisfaction and constitutes a significant amount, up to 55%, of warehouse operational expenses [1]. Inefficiencies in order picking can result in prolonged walking time, non-value-adding tasks, and thus, decreased workforce utilization [2], which similarly affects middle-mile routing inefficiencies within wider logistical operations. Multiple studies have attempted to improve order picking performance using either simulation-based modelling [3] or optimization approaches to enhance routing sequences and layout design [4-5]. However, these approaches are frequently applied independently, limiting the ability to validate algorithmic improvements under realistic operational conditions. Moreover, while some studies examine factors like order size, pick station location, and routing strategies they often do so under fixed conditions without experimental design to assess factor interactions. For instance, placing collecting points too far from picking zones significantly increases walking distance and reduces productivity [6]. Inefficient picking sequences have also been shown to cause duplicate walking or searching [7]. Recent efforts, such as applying class-based storage or real-time tracking systems, have proven effective in reducing search or idle time [8]. However, these solutions are rarely tested within complex real-world layouts, and few studies critically compare multiple metaheuristic optimization methods under variable picking conditions [9].

Despite these advancements, important methodological gaps remain. First, simulation and optimization techniques are often implemented separately [10], restricting comprehensive evaluation of their combined impact on labour utilization. Second, interaction effects among key operational factors—such as order size, collecting point placement, and routing strategies—are seldom analyzed using factorial experimental design. Third, comparative benchmarking of multiple metaheuristic algorithms under identical warehouse conditions remains limited, making contextual algorithm effectiveness difficult to assess. As a result, existing studies may overlook combined effects that influence labour efficiency and may not fully validate optimization outcomes within realistic operational environments.

This study introduces a novel hybrid framework that integrates discrete-event simulation, factorial experimental design, and four metaheuristic algorithms: Tabu Search, Hill Climbing, Simulated Annealing, and Particle Swarm Optimization to investigate and enhance labour utilization in order picking operations. A real mezzanine warehouse case study is employed to examine how order size, collecting point location, and picking sequence jointly influence the proportion of value-added picking time relative to total working time.

The objective of this research is to investigate the determinants of labour utilization in manual order picking operations by systematically analyzing how operational design factors affect the ratio of value-added picking time to total working time. This performance indicator is computed as shown in the following equation.

$$\text{Labour Utilization (\%)} = \frac{T_p}{T_p + T_s + T_w + T_d} \times 100 \qquad (1)$$

where T_p is the Picking time, T_s is the Scouring Time, T_w is the Walking Time, T_d is the Idle-Time. From the equation above, the percentage of labour utilization will increase only when employees dedicate most of their time to valuable activities, specifically picking time, rather than to scouring time, walking time, or waiting time. However, walking time remains as high as fifty-five percent of warehouse order picking cost because of inefficient storage and unoptimized picking routes, leading to labour utilization levels that are lower than optimal [11].

There is a notable scarcity of empirical research in the field of warehouse operations that combines metaheuristic optimization with simulation-based evaluation to enhance labour utilization. While prior studies have addressed order picking efficiency, few have examined the interaction effects of key operational factors—such as order size, collecting point location, and picking sequence—through a structured experimental approach. This research contributes by developing a replicable hybrid framework that integrates simulation, metaheuristics, and Design of Experiments (DOE), providing both methodological and practical insights into optimizing manual, labour-intensive warehouse systems under space and resource constraints.

2.0 Research Methodology

The methodology employed in this study adopts a structured and integrated framework that combines discrete-event simulation with metaheuristic optimization, guided by principles of experimental design [12]. Warehouse order picking in picker-to-parts systems can be formulated as a combinatorial routing problem, where the number of possible picking sequences increases exponentially with order size. In such contexts, exact optimization methods may become computationally intensive, particularly when embedded within simulation-based evaluation. Therefore, metaheuristic approaches are adopted due to their scalability, flexibility, and demonstrated effectiveness in solving routing and sequencing problems in warehouse environments. The selection of metaheuristic algorithms in this study is based on their distinct search mechanisms and complementary exploration–exploitation characteristics. Hill Climbing (HC) is included as a baseline local search heuristic. Tabu Search (TS) incorporates memory structures to prevent cycling and has been widely applied in routing and scheduling optimization. Simulated Annealing (SA) introduces probabilistic acceptance criteria to escape local optima in complex search landscapes. Particle Swarm Optimization (PSO), a population-based global search algorithm, has shown strong performance in warehouse routing and batching contexts [13-14]. By benchmarking these four algorithms under identical experimental conditions, this study enables systematic comparison of their contextual effectiveness in improving labour utilization.

As illustrated in Figure 1, the process begins with the development of a simulation model in FlexSim to replicate real-world warehouse operations and generate picking list data based on predefined order distributions. The generated data are subsequently transferred to Python, where four metaheuristic algorithms—Hill Climbing (HC), Tabu Search (TS), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) presented in Table 1,
Table 2,
Table 3 and
Table 4, respectively, are applied to optimize the sequence of item retrieval by minimizing total travel distance [15]. The optimized sequences are then re-imported into FlexSim to simulate the revised picking process. This closed-loop integration enables iterative evaluation and refinement, capturing the interaction between algorithmic solutions and operational performance. Experimental scenarios are structured using a full factorial Design of Experiments (DOE) to analyze the effects of key factors and their interactions. The simulation outputs—including labour utilization, walking time, and total travel distance are recorded for each experimental condition.

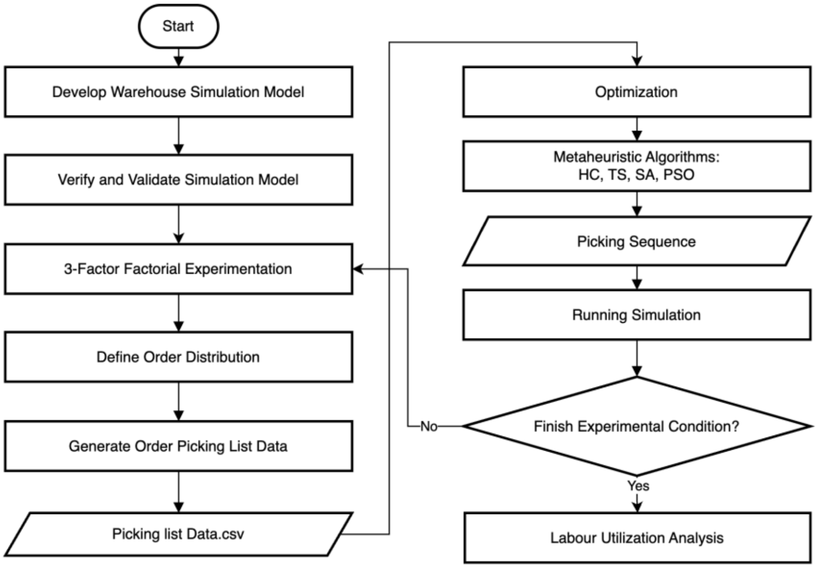

Figure 1: Integration framework between simulation and metaheuristic optimization using Python algorithms (HC, TS, SA, PSO) with experimental design.

This section outlines the key data inputs and assumptions used in developing the simulation model. The model parameters were derived from historical operational records and time study data collected from the case company. These data include total picking time per order, order profiles, and average picker walking speed. The following assumptions were adopted to ensure controlled and reproducible simulation conditions:

- Inventory availability is assumed to be sufficient; all requested products are always available for picking, and stockouts are not considered.
- The warehouse operates with four pickers. Each picker follows a pick-by-order policy, meaning that one order is completed before proceeding to the next.
- The quantity of packaging picked exactly matches the demand specified in each order; no picking errors or quantity deviations are modeled.

These assumptions reflect the operational characteristics of the case warehouse and enable focused evaluation of routing strategies and layout configurations without interference from inventory or behavioral uncertainties.

Table 1: Algorithm I. Hill Climbing

Algorithm I. Hill Climbing Algorithm

```
Initialize the best_order as the initial order
Calculate best_distance based on best_order
Set max_iterations ← number of locations × 1000
for iteration = 1 to max_iterations do
    Randomly select two different positions pos1 and pos2 (excluding start and end)
    Create new_order by swapping pos1 and pos2 in best_order
    Calculate new_distance based on new_order
    if new_distance < best_distance then
        Update best_order ← new_order
        Update best_distance ← new_distance
    end if
end for
Output the best_order and best_distance
```

Table 2: Algorithm II. Particle Swarm Optimization

Algorithm II. Particle Swarm Optimization Algorithm

```
Initialize particles as random permutations of order (excluding first and last)
Set num_particles ← max(10, number of locations ÷ 2)
Calculate personal_best and personal_best_distance for each particle
Identify global_best among all particles
Set max_iterations ← number of locations × 1000
For iteration = 1 to max_iterations do
    For each particle do
        Generate a new random permutation
        Calculate new_distance
        If new_distance < personal_best_distance then
            Update personal_best and personal_best_distance
            If new_distance < global_best_distance then
                Update global_best and global_best_distance
            End If
        End If
    End For
End For
Output global_best path and distance
EndAlgorithm
```

Table 3: Algorithm III. Tabu Search

Algorithm III. Tabu Search

```
Initialize best_order as a copy of order
Calculate best_distance based on best_order
Initialize tabu_list as an empty list
Set tabu_size ← 10
Set max_iterations ← number of locations × 1000
For iteration = 1 to max_iterations do
    Randomly select two different positions pos1 and pos2 (excluding first and last)
```

```
8.     Create candidate_order by swapping pos1 and pos2 in best_order
9.     Calculate candidate_distance
10.    If candidate_order not in tabu_list or candidate_distance < best_distance then
11.        Update best_order ← candidate_order
12.        Update best_distance ← candidate_distance
13.    End If
14.    Add candidate_order to tabu_list
15.    If size of tabu_list > tabu_size then
16.        Remove the oldest entry from tabu_list
17.    End If
18. End For
19. Output best_order and best_distance
EndAlgorithm
```

Table 4: Algorithm IV. Simulated Annealing

Algorithm IV. Algorithm Simulated_Annealing

```
Algorithm Simulated_Annealing(order, distance_matrix)
1. Initialize current_order as a copy of order
2. Calculate current_distance
3. Initialize best_order ← current_order
4. Initialize best_distance ← current_distance
5. Set max_iterations ← number of locations × 1000
6. Set initial_temperature ← max_iterations + 1
7. For iteration = 1 to max_iterations do
8.     If temperature ≤ 1 then
9.         Break
10.    End If
11.    Randomly select two different positions pos1 and pos2 (excluding first and last)
12.    Create new_order by swapping pos1 and pos2 in current_order
13.    Calculate new_distance
14.    If new_distance < best_distance then
15.        Update current_order ← new_order
16.        Update current_distance ← new_distance
17.        Update best_order ← current_order
18.        Update best_distance ← current_distance
19.    Else
20.        Compute acceptance_probability ← exp(−(new_distance − best_distance) / temperature)
21.        If random(0,1) < acceptance_probability then
22.            Update current_order ← new_order
23.            Update current_distance ← new_distance
24.        End If
25.    End Else
26.    Decrease temperature by 1
27. End For
28. Output best_order and best_distance
EndAlgorithm
```

3.0 Experiment Design

This study employs a full factorial Design of Experiments (DOE) to systematically evaluate the effects of operational design factors on Labour Utilization (%). The experimental design investigates three independent factors: (A) Items per Order, (B) Collecting Point Location, and (C) Picking Sequence Algorithm, as shown in Table 5. Labour Utilization (%) is defined as the response variable.

The experimental structure follows a 3-factor factorial design with Factor A at 3 levels, Factor B at 2 levels, and Factor C at 4 levels, yielding 24 unique treatment combinations. The full factorial approach was selected to enable estimation of all main effects, two-way interaction effects (A×B, A×C, B×C), and the three-way interaction effect (A×B×C). This design ensures comprehensive evaluation of how operational factors jointly influence labour utilization. Each experimental scenario was simulated for 50 replications to reduce stochastic variability and enhance statistical reliability. Consequently, the total run numbers conducted in this study equals 24 × 50. The replication number was determined based on preliminary pilot simulations to ensure stable mean estimates of labour utilization.

Table 5: General Full Factorial Design

Design Factor	**Factor Levels**			
A: Items per Order	[1,5)	[5,10)		[10-15)
B: Collecting Point	Current Point		Middle Point	
C: Picking Sequence Algorithm	Tabu Search	Hill Climb	Simulated Annealing	Particle Swarm Optimization

The factor levels were selected to reflect realistic operational conditions of the case warehouse. The "Items per Order" factor represents low-, medium-, and high-demand scenarios observed in historical data. The "Collecting Point" factor compares the existing operational layout with a proposed middle-point configuration aiming to reduce walking distance. The "Picking Sequence Algorithm" factor evaluates four distinct metaheuristic search strategies with different exploration–exploitation characteristics. These levels ensure practical relevance and enable systematic comparison across operational scenarios. Key factors impacting labour utilization include the number of items per order, which influences walking time, as more items require employees to travel to multiple locations. Strategically, placing drop-off stations and collecting points can further reduce walking distance. Figure 2 illustrates the position of the collecting point, designated as the current collection point (Current-point), which serves as the collection location for packages retrieved from the storage area , and the mid-point of the warehouse (Mid-point), which represents the new location to simulate the relocation of the collection location for packages retrieved from the storage area for combining on a pallet. Additionally, an effective picking sequence algorithm can optimize routes for order picking, decreasing walking distance and enhancing overall labour utilization.

The experimental results were analyzed using Analysis of Variance (ANOVA) to determine the statistical significance of main and interaction effects. The significance level was set at $\alpha = 0.10$, indicating the confirmatory nature of industrial experimentation. Effect interpretation focuses not only on statistical significance but also on practical relevance in operational performance.

Figure 2: Collecting Point

4.0 Results

The analysis of variance (ANOVA) results indicate that the three main factors—Items per Order, Collecting Point Location, and Picking Sequence Algorithm—significantly affect Labour Utilization at the $\alpha = 0.10$ significance level. This confirms that variations in operational design decisions systematically influence the proportion of value-added working time. In terms of interaction effects, the 2-way interaction between the number of items per order and the collecting point was significant (P-value = 0.080), as was the 3-way interaction between all three factors (P-value = 0.050), as displayed in Table 6. These results indicate that each factor not only puts forth a direct influence on labor utilization but also produces interaction effects. This is particularly evident when the number of items per order increases, and a mid-point collection strategy is employed alongside a suitable algorithm, which can substantially enhance labor utilization, as shown in Figure 4.

Table 6 Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	23	3112.390	135.320	98.290	0.000
Linear	6	3071.090	511.850	371.780	0.000
Items per Order	2	1123.720	561.860	408.100	0.000*
Collecting Point	1	1425.090	1425.090	1035.100	0.000*
Picking Sequence	3	522.280	174.090	126.450	0.000*
2-Way Interactions	11	23.190	2.110	1.530	0.133
Items per Order x Collecting Point	2	7.130	3.560	2.590	0.080*
Items per Order x Picking Sequence	6	10.150	1.690	1.230	0.298
Collecting Point x Picking Sequence	3	5.910	1.970	1.430	0.239
3-Way Interactions	6	18.110	3.020	2.190	0.050
Items per Order x Collecting Point x Picking Sequence	6	18.110	3.020	2.190	0.050*
Error	96	132.170	1.380		
Total	119	3244.560			

*Significance level is 0.10

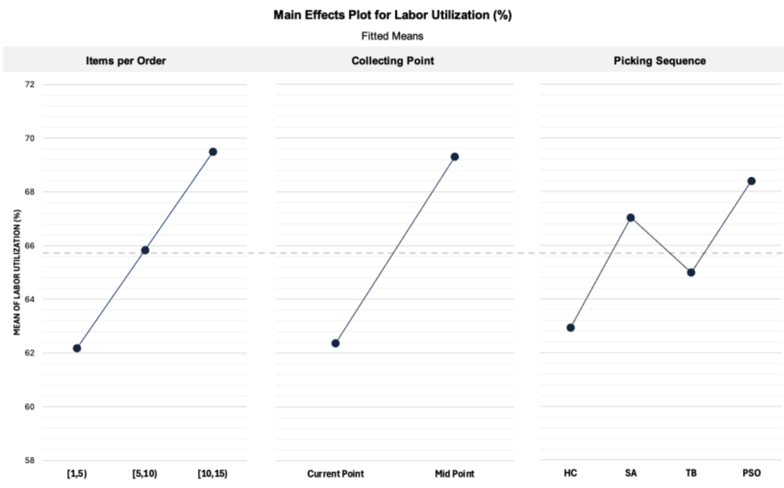

Figure 3: Main Effects Plot for Labour Utilization (%)

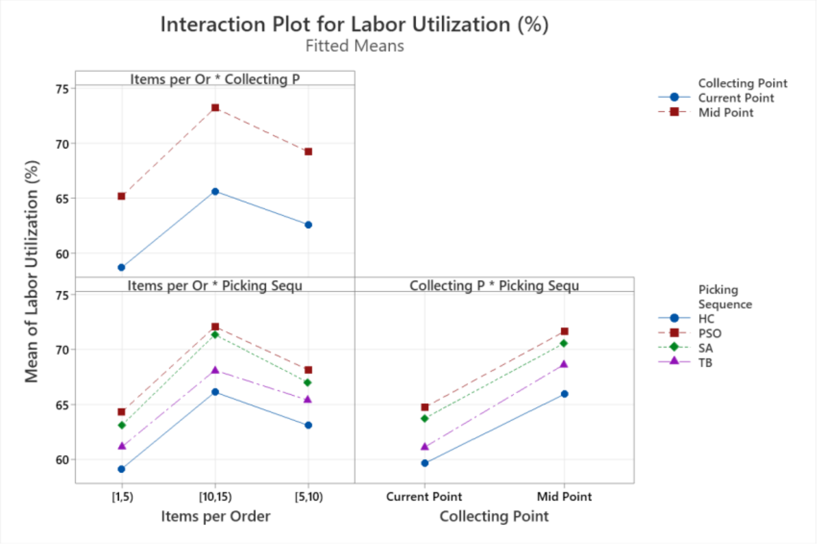

Figure 4: Interaction Plot for Labour Utilization (%)

4.1 Items per Order Effect

The number of Items per Order is an influencing factor on Labour Utilization (%). Figure 4 demonstrates a positive relationship between the number of items per order and labour utilization. This effect can be explained by the relative increase in value-added picking time compared to fixed walking components, thereby improving the ratio of productive time to total working time. The higher the number of Items per Order, the better the labour utilization. This factor was brought to the study's attention because labour utilization realization is particularly important in labour resource planning, especially in manual order picking operations. Normally, the number of Items per Order is driven by the customers' behavior which highly impacts the picking system. Thus, the simulation result shows that the maximum labour utilization of the system, which is less than 70%, still has the capacity left to handle in case demand increases. This finding aligns with Bertolini, et al. [13], who reported that increasing batch size enhances picking efficiency by concentrating operational effort on value-added activities. However, unlike prior studies that primarily measure travel distance reduction, this study demonstrates how order size interacts with layout configuration and routing algorithm to influence labour utilization structurally. In practical warehousing, this indicates that promoting larger batch orders or dynamic consolidation could be a successful strategy to improve labour efficiency without significant investments in new technology.

4.2 Picking Sequence Algorithm Effect

The Picking Sequence factor significantly affects labour utilization, at a significant level of 0.10. The algorithms experimented in the study, illustrated in Table 1,
Table 2,
Table 3 and
Table 4, respectively. Figure 3 illustrated Particle Swarm Optimization (PSO) excels in identifying the shortest path, resulting in reduced walking time for pickers and expedited item retrieval. Simulated Annealing (SA) generates results comparable to PSO; however, it is prone to becoming trapped in local optimum values. Tabu Search (TB) can avoid unsuitable paths to a certain extent, yet it encounters challenges in identifying the optimum solution. In contrast, Hill Climbing (HC) produces the least favorable outcomes, as it tends to become trapped in local optima, limiting its ability to explore more efficient alternative routes. The superior performance of PSO observed in this study is consistent with findings reported by Gülyeşil and Durmuşoğlu [14], who highlighted the effectiveness of population-based metaheuristics in complex routing environments. However, this study extends prior work by benchmarking PSO alongside HC, TS, and SA under identical factorial experimental conditions, thereby enabling contextual performance comparison rather than isolated evaluation.

4.3 Collecting Point Effect

The result shows that the Collecting Point had a significant impact, which will cause labour utilization to be different at a 0.10 significance level, compared between Mid-Point and Current Point. Selection of the Mid-Point location resulted in significantly reduced walking distance for employees because products were placed in a more accessible location, which reduced the walking time and tended to increase the percentage labour utilization, as shown in Figure 2. The improvement observed under the Middle Collecting Point configuration can be attributed to the reduction in average walking distance per pick cycle, thereby increasing the proportion of value-added picking time relative to total working time. This supports findings by Winkelhaus, et al. [16], who indicated that rearranging collecting zones in a hybrid picking system resulted in a 20–27% decrease in non-productive movement. This underscores the fact that layout change, especially concerning staging and collecting locations, can result in measurable labour reductions even in low-tech, manual warehouses.

4.4 Interaction Effect

Interaction effects in the experimental model include 2-factor interaction and 3-factor interaction. Figure 4 indicates that both the interaction of "Items per Order" and "Collecting Point", as well as the interaction of "Items per Order", "Collecting Point", and "Picking Sequence" exhibit significant interaction effects at a significance level of 0.10. An analysis of the interaction plot illustrated in Figure 4 for "Items per Order" and "Collecting Point" reveals that the "Collecting Point" should be designated as "Middle Point" for orders comprising a substantial quantity of items, specifically between 10 to 15 in this study. This configuration optimizes labour utilization, as it facilitates enhanced accessibility to storage locations for pickers compared to the "Current Point." Consequently, when dealing with a larger volume of items to be picked, the "Middle Point" location significantly minimizes the walking distance required by employees. An extensive analysis of the interaction between "Items per Order," "Collecting Point," and "Picking Sequence" reveals that the combination of the "Middle Collecting Point" and the "PSO Picking Sequence" consistently results in the highest labour utilization across all levels of "Items per Order." This pattern suggests that a rise in the number of items per order improves the efficiency and productivity of the order picking procedure for this particular combination. Thus, the implementation of the "Middle Collecting Point" in conjunction with the "PSO Picking Sequence" is the most effective strategy for optimizing order picking operations, consequently enhancing labour productivity and operational outcomes. **Error! Reference source not found.** depicts the average labour utilization across all scenarios, ranging from approximately 55% to 77%. This range indicates potential for improvement, particularly in situations aimed at optimizing worker utilize. The factors designated as "Middle Collecting Point" and "PSO Picking Sequence," regardless of the number of items picked per order, are the most effective variables in improving labour utilization compared to others. This highlights the necessity of recognizing factor interactions, as observed by Leon, et al. [12], who emphasized that simulation-optimization research must include interaction effects to prevent erroneous conclusions from isolated component analysis. This suggests that leaders ought to avoid executing routing algorithms or layout modifications alone; instead, they should employ rigorous Design of Experiments (DOE) testing to identify optimal combinations.

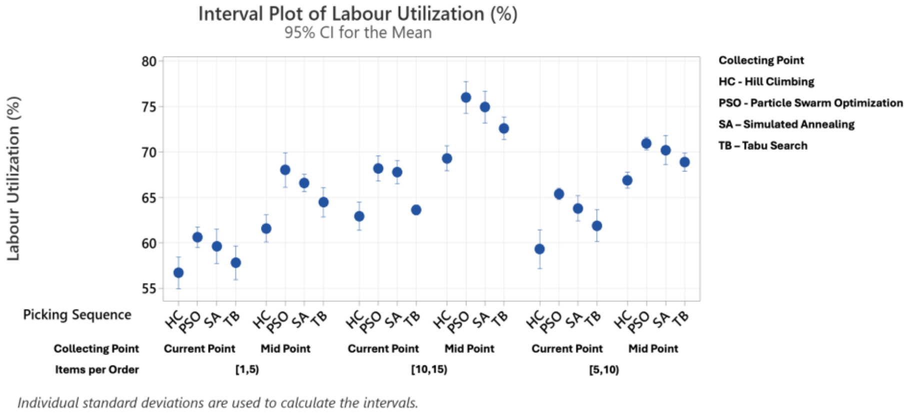

Figure 5: Interval Plot of Labour Utilization (%)

5.0 Conclusion

This study investigated operational strategies to enhance labour utilization in manual order picking systems through the integration of simulation, factorial experimentation, and metaheuristic benchmarking. The research utilized computer modelling and design of experiments (DOE) to analyze aspects influencing labour utilization, including the number of orders, the location of collection locations, and picking routing algorithms. The findings demonstrate that labour utilization is significantly influenced not only by individual operational factors but also by their interaction effects. The optimal configuration—combining the Middle Collecting Point with PSO-based routing consistently yielded the highest labour utilization across varying order sizes and adeptly addresses the expected substantial increase in the volume of selecting items caused by client requests.

From a scientific perspective, this study advances warehouse optimization research by introducing an interaction-aware evaluation framework that integrates discrete-event simulation with full factorial Design of Experiments and multi-metaheuristic benchmarking. Unlike prior studies that focus primarily on routing distance or throughput metrics, this research conceptualizes labour utilization as a structural performance indicator and demonstrates the importance of coordinated operational decision-making.

Practically, the results provide evidence-based guidance for warehouse managers operating in labour-intensive environments. The findings indicate that significant efficiency gains can be achieved through strategic layout positioning and routing optimization without requiring capital-intensive automation technologies. This offers a scalable and economically feasible pathway for performance improvement, particularly for traditional manufacturing warehouses.

Despite its contributions, this study has several limitations. First, the simulation model assumes a fixed warehouse layout and constant worker speed, which may not fully capture dynamic congestion or behavioral variability. Second, scalability to large-scale multi-picker environments was not evaluated. Third, the computational performance of the metaheuristic algorithms was assessed within the experimental scope but not benchmarked for real-time implementation constraints. These limitations suggest caution when generalizing results to highly automated or large-scale distribution centers.

Future research should explore multi-picker environments, dynamic demand scenarios, and integration with real-time data systems aligned with Industry 4.0 initiatives. Extending the framework toward multi-objective optimization models that incorporate energy consumption, carbon footprint, and order accuracy may further enhance sustainable warehouse performance. Additionally, hybrid approaches combining manual optimization strategies with autonomous systems warrant further investigation. In Addition, it should focus on advancing sustainable order picking optimization by integrating automation and artificial intelligence (AI) to enhance labour efficiency while minimizing environmental impact [17]. To align with Industry 4.0 initiatives, further studies should explore multi-picker environments, dynamic demand scenarios, and the integration of real-time data systems . The deployment of Autonomous Mobile Robots (AMRs) and Automated Guided Vehicles (AGVs), combined with AI-driven routing algorithms that can learn and anticipate picking demands in real time, offers a significant opportunity to reduce worker walking lengths and wasteful energy consumption [18]. Additionally, hybrid approaches that combine manual optimization strategies with autonomous systems warrant further investigation to identify the most effective operational configurations. To promote Green Warehousing and Net Zero Logistics, future frameworks should be extended toward multi-objective optimization models that simultaneously account for manpower consumption, energy use, carbon footprint, and order accuracy. Finally, the development of a robust Decision Support System (DSS) based on these sustainability criteria will enable warehouses to transition efficiently into the era of Smart Warehousing and Logistics 5.0. This evolution will not only reduce environmental impacts but also significantly improve the competitiveness and responsiveness of future logistics systems.

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AUTHOR CONTRIBUTIONS

P.Sukjumrat: Conceptualization, Methodology, Writing- Original Draft Preparation, Data Curation, Validation, Reviewing and Editing; N.Khunjan: Conceptualization; N.Sirivongpaisal and S.Suwatcharachaitiwong: Conceptualization, Data Curation, Validation, Supervision and Reviewing and Editing.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the manuscript.

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