# An Approach to Bias Mitigation in Warehouse Productivity Consideration

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## Abstract

The performance assessment of warehouse workers plays a vital role in enhancing logistics industry productivity. While conventional methods emphasize single-output to single-input calculations, worker performance is multifaceted, influenced by various factors such as experience, fitness, training, and welfare. Existing literature predominantly focuses on optimizing warehouse layouts and processes but neglects the issue of bias in worker performance evaluations. Thus, this study aims to explore and innovate an approach to worker performance evaluation, considering task allocation balance, traveling distances, and additional factors influencing worker productivity. Leveraging data from a disparities 3PL service company, the research employs exploratory data analysis, shortest path calculation for expected traveling distance, and a bias mitigation calculation to unveil disparities and propose a more equitable performance assessment model. The findings highlight the significance of refining performance evaluation methodologies to foster fairness, ultimately augmenting warehouse productivity. Future research directions involve expanding data analysis, considering vertical dimensions, and incorporating real-time tracking systems for comprehensive insights into warehouse operations.

**Keywords**: logistics, warehouse, productivity, data analysis, Dijkstra's

## 1. Introduction

Warehouse operations rely heavily on the efficiency and effectiveness of labor, making the performance assessment of warehouse workers a critical aspect of productivity enhancement in the logistics industry [5]. Stated by Johnson et al., 2010, industries commonly use partial productivity method by calculating the level of a single output generated compared to the level of a single input consumed [7], for example, using number of completed pallets comparing to working hours when calculating warehouse worker performance. However, warehouse worker performance is influenced by many factors. It can be influenced by work experience, physical fitness, financial reward, training, and welfare as studied by Prasadika et al., 2018 [6] or the factors in term of safety (accidents) and foreign worker (language barrier) which reported by Karim et al., 2018 [5]. In addition, in the context of warehouse operations the type of products being managed slightly impacts the performance of workers as well [6].

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Numerous studies have delved into the factors affecting warehouse productivity, often emphasizing the optimization of layouts and processes to minimize costs [3, 9] including considering both ergonomic and economic perspective [8]. Despite the extensive literature on improving warehouse productivity through layout optimization and process enhancement, the aspect of bias mitigation in worker performance calculation remains notably absent. Bias in these evaluations can lead to disparities in performance assessment among workers, impacting morale, motivation, and overall fairness in the workplace. In response to this gap, this paper aims to explore and innovate an approach for evaluating performance that surpasses the limitations of existing calculation methodology to ensure fairness and equity among workers, ultimately enhancing overall productivity.

## 2. Related Works

### 2.1 Warehouse Productivity

[5] The study investigated warehouse productivity failure factors in Malaysia's logistics service sector using a Fuzzy Analytic Hierarchy Process (F-AHP) method. It identified the top three influential factors as 'labor productivity', 'warehouse utilization', and 'inventory space utilization'. The methodology involved expert interviews and a pair-wise comparison analysis. Labor productivity was attributed to skilled worker recruitment, training in safety standards, and standardized language in the workplace. Warehouse utilization improvement suggestions included adopting effective Warehouse Management Systems (WMS) and modern technology integration. Inventory space utilization recommended warehouse layout redesign and renting unused space to optimize storage. Stated by researchers, the limitations existed due to limited local literature, and future research should focus on validating these findings and exploring additional factors for comprehensive improvement strategies in the logistics industry.

[6] The study explores the relationship between various factors and picker performance in 3PL warehouses. It identifies twelve crucial factors categorized as picker-related (work experience, physical fitness, financial reward, training, welfare), management-related (leadership, organizational culture), and warehouse-related (storage assignment, order batching, facility safety, working environment, technical facilities). Using Partial Least Squares - Structural Equation Modelling (PLS-SEM), the research indicates that picker-related and warehouse-related factors significantly impact picker performance, while management-related factors have a lesser effect. Moreover, the analysis introduces product types (Fast Moving Consumer Goods (FMCG) and others) as a moderator influencing these relationships. The research methodology involves expert opinions, literature review, and data collection from top Third-party logistics (3PL) services companies in Sri Lanka. The findings underscore the critical importance of recognizing these factors to enhance picker performance, subsequently improving warehouse efficiency and customer satisfaction in Sri Lanka's 3PL industry.

Table 1 is the summary of warehouse productivity’s literature review, they show that labor productivity is the crucial factor affecting warehouse productivity. In addition, labor productivity can be influenced by many factors. The focus one is the picker-related category which contains factors as follow, work experience, physical fitness, financial reward, training, and welfare.

Table 1 Summary of related works: warehouse productivity

| Ref. | Year | Objectives | Methods | Key Factors |
|---|---|---|---|---|
| [5] | 2018 | To assess failure factors from ten of warehouse productivity in Malaysia logistics service sector | F-AHP (expert interviews and a pair-wise comparison analysis) | 1. Labor Productivity 2. Warehouse Utilization 3. Inventory Space Utilization |
| [6] | 2022 | To identify relationship between various factors and picker performance | PLS-SEM | picker-related, management-related, and warehouse-related categories |

### 2.2 Traveling Distance Calculation

Numerous studies aiming to enhance warehouse efficiency often employ Graph, a data structure used for computational purposes [2][3][4]. Among the well-known algorithms in this domain is Dijkstra's Algorithm [1], categorized as a greedy algorithm type. Greedy algorithms solve problems by selecting the best available option in the present moment, without considering if the current best choice will lead to the overall optimal outcome. Dijkstra's Algorithm is particularly renowned for determining the shortest path from a source node to all other nodes within a Graph (single source shortest path), primarily suitable for undirected Graphs with positive weights. However, it's important to note that this algorithm operates effectively only on positive weighted Graphs, and its speed in finding a solution is contingent upon the number of nodes present in the Graph.

## 3. Methods

Figure 1 presents workflow diagram of this work, the details as following.

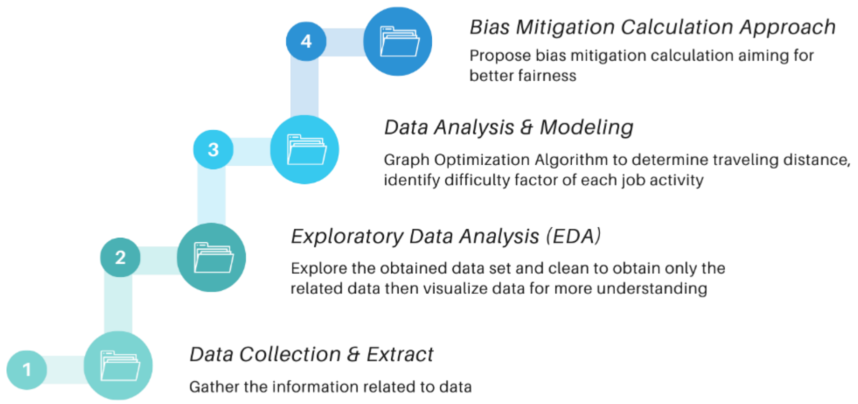

Figure 1 Workflow Diagram

### 3.1 Data Collection and Extraction

#### 3.1.1 Business Data

Data is generously provided by one of 3PL service company in Thailand. The consumer goods warehouse has a total space of 52,913 sq.m. which in this work only studied in the focused area approximately 588 sq.m. highlighted as orange box in Figure 2. The warehouse rack has 7 levels. There are 4 job activities, Picking, Putaway, Replenishment, and Transfer. The given data is only the data of full pallet completed order which worker always utilizes material handling equipment (MHE) to handle. It is filtered to obtain only the orders that its source bin or destination bin is in the focused area.

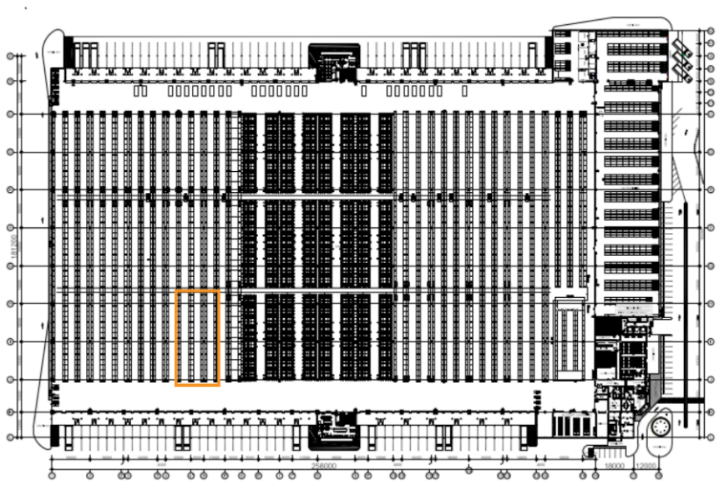

Figure 2 Warehouse Layout

#### 3.1.2 Programming Language and Libraries

Python 3.11.3 was used in this work. Its libraries are used as follows. Numpy and Pandas are for managing data. Matplotlib.pyplot and Seaborn are for visualizing data. Networkx is for graph creation and shortest path algorithm.

#### 3.1.3 Dataset

1) Raw data from WMS

Raw data has been given in two files, transaction data of Putaway, Picking, and Transfer activity and transaction data of Replenishment activity. Both files have data limitations. The order created date and time data from these datasets cannot be used as the problem of time zone setting and data inconsistency (after verification) leading to use of data from system’s log file to gather order created/completed date and time.

2) Log file

WMS log data which only is available from 08 - 30 Sep 2023 due to system auto deletion setting. Another data limitation is some transfer activities, this log file does not contain its record as it links and is recorded in other system.

### 3.2 Exploratory Data Analysis (EDA)

#### 3.2.1 Clean and Interpret Data in Transaction Files

Data has been cleaned and interpreted according to the information given by the company by dropping hoax/dummy order (Does not count in performance calculation), identify job activity of each order in transaction files, and then concatenate data from both transaction files into 1 dataframe (select only competed date since 08-30 Sep 2023).

#### 3.2.2 Extract Data from Log File (Date and Time)

The timestamp of each order has been extracted from log file by manually identified specific pattern of each job activity. After that the obtained data is joined into the transaction dataframe. The working duration of each assigned order has been calculated from the time difference between start and finish timestamp. All data that cannot detect timestamp from log file has been dropped.

### 3.3 Data Analysis and Modeling

#### 3.3.1 Data for Graph Creation

Figure 3 shows the measurement of warehouse rack dimensions. The nodes of the Graph which are shown in the Figure 3 represent as each location in warehouse focused area marked at the middle of rack’s location. The aisle of warehouse designated as 2 ways path, so the Graph is created as undirected Graph.

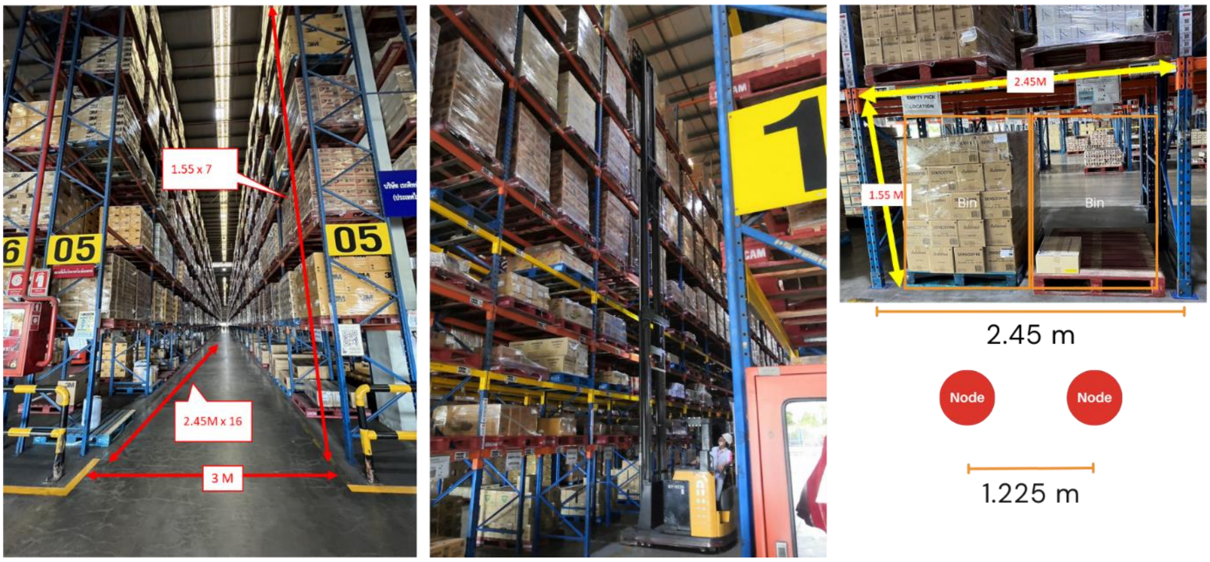


Figure 3 Data from Graph creation

#### 3.3.2 Graph Creation and Distance Calculation

Since traveling way between each node is varied, two Graph patterns have been proposed as shown in Figure 4 according to the focused area layout to find which one will give a lower distance when traveled. The in and out (I/O) point is set to be the same point at the middle of focused area. The weight of the Graph is marked as the distance value between each node.

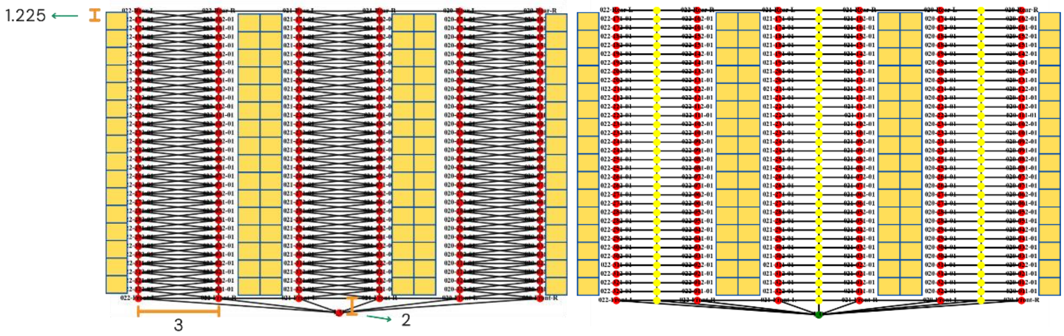


Figure 4 Graph pattern 1 (left) and Graph pattern 2 (right)

Dijkstra's algorithm is used to determine the shortest path and calculate the traveling distance (weight of the Graph). The 1st calculation approach is done by calculating distance per date of each worker by not separate activities, and the 2nd calculation approach is done by calculating distance per order of each worker by separate activities as shown as example in Figure 5. Both of the calculation approaches gave the same total distance, but the 2nd calculation approach is used when trying to analyze or compare between activities. The calculated weight (distance) only considers 2D, which currently does not consider the difference of rack levels. Since there is transaction data that the source or destination bin is a dummy bin (pallet is store at the area which has not been set the location in WMS, for example when overflow occurs.), if found the location will be set to be at node I/O. Moreover, if the source or destination bin is not in the focused area, it will be set to be node I/O.

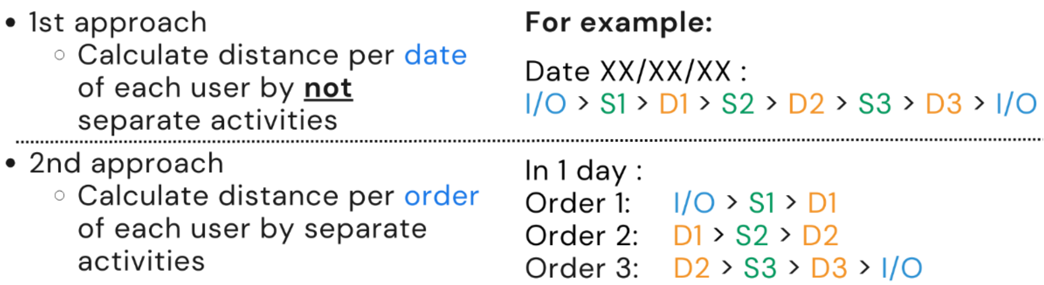


Figure 5 Examples of distance calculation approach (S = Source bin, D = Destination bin)

### 3.4 Bias Mitigation Calculation Approach

In table 2 it shows the current company minimum target of each activity and company current worker performance calculation. The working hours of company current calculation is the assumption of working time for example 8 working hours per working day. As the data limitation, our calculation for comparing to company minimum target is slightly different from company current calculation by using total operate time instead or working time in company current calculation. The total operate time is obtained from the sum of time difference between start and completed timestamp from the log file. Lastly, we proposed adding a distance difficulty factor as one of the factors which minimize the bias in worker performance calculation. The calculated distance is separated into 3 categories which are short, medium, and long distance separated by percentile as indicated in table 2. The value of distance difficulty factor used in this work for short, medium, and long distance are 3 of these set of values respectively, (0.50, 1.00, 1.50), (0.25, 1.00, 1.75), and (0.75, 1.00, 1.25). Comparing our calculation and added distance difficulty factor calculation to company minimum target and median, the results is calculated to be in percentage that each worker performance (number of completed order) higher than the comparing one with the setting threshold at 95%.

Table 2 Performance Calculation and company minimum target

<table>
<tr><td>Company Minimum Target</td><td>100 case/hr -> 3 pallet/hr<br>(30 cases/pallet)</td><td colspan="2">17 pallet/hr</td></tr>
<tr><td>Method</td><td>Picking</td><td>Putaway</td><td>Replenishment</td></tr>
<tr><td>Company current calculation</td><td colspan="3">Number of completed pallets / Working hour</td></tr>
<tr><td>Our calculation</td><td colspan="3">Number of completed pallets / Total operate time</td></tr>
<tr><td rowspan="2">Added distance difficulty factor</td><td colspan="3">Number of completed pallets / Total operate time * Difficulty Factor</td></tr>
<tr><td colspan="3">Separate by Percentile<br>Short: < 33<br>Medium: >= 33 and <= 66<br>Long: > 66</td></tr>
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## 4. Results and Discussion

### 4.1 Visualize Transaction Data

Figure 6 presents that there is a high variation of assigned task of each activity between workers. It is an indication of imbalanced task assignment.

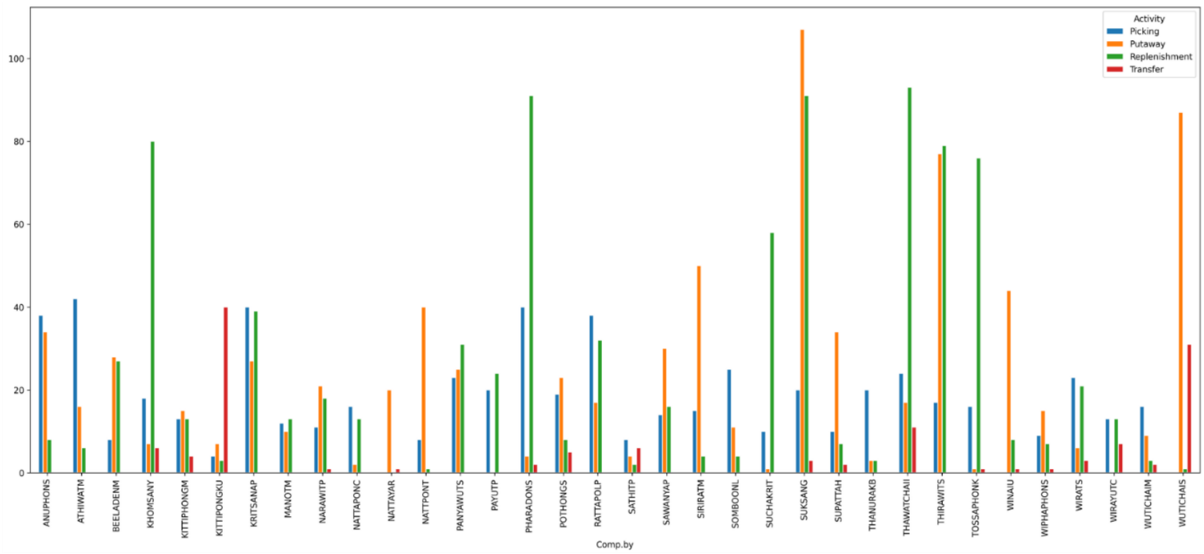

Figure 6 Visualize transaction data in September 2023, number of completed orders of each worker

### 4.2 Graph pattern comparison and traveling distance calculation

Comparing proposed Graph pattern 1 and 2, the result shows that Graph pattern 1 gave the total distance (in meters) shorter than Graph pattern 2 as shown in Table 3 using 1st calculation approach. Thus, Graph pattern 1 is used in this work to calculate the expected traveling distance of each worker in further analysis.

Table 3 Result of total distance from Graph pattern 1 and 2

| Graph pattern | Total Distance (m) |
|---|---|
| 1 | 68,888.11 |
| 2 | 73,759.31 |

By visualizing the calculated traveling distance of each activity using the 2nd calculation approach, the result is shown as Figure 7. The data demonstrates the uneven distance per order between each worker in each activity. However, since the scarce data of transfer activity caused by lack of timestamp from the given log file. So, this work did not further analysis on this transfer activity.

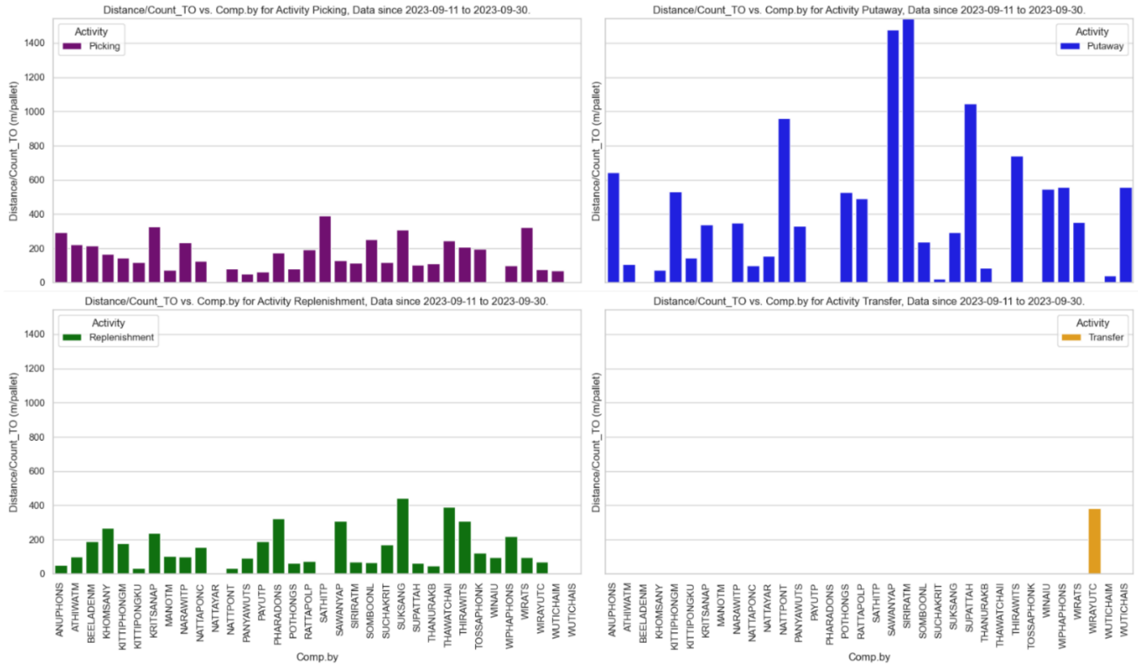

Figure 7 Visualize traveling distance of each worker in each activity, Picking (top left), Putaway (top right), Replenishment (bottom left), and Transfer (bottom right)

Figure 8 shows mean, median, mode, and standard deviation including histogram of completed time per pallet and calculated traveling distance per pallet. Shapiro-Wilk test is used for normality hypothesis testing 95% confidence level for calculated traveling distance per pallet of Picking, Putaway, and Replenishment activity, the p-value are 5.976*10^-7, 0.0007, and 0.007 respectively. The results show that null hypothesis is rejected.

| | Cal | time_diff | Distance(m) |
|---|---|---|---|
| Activity | | | |
| Picking | Mean | 155.544000 | 50.501550 |
| Picking | Median | 88.000000 | 49.100000 |
| Picking | Mode | 17.000000 | 58.848858 |
| Picking | SD | 252.546332 | 21.516256 |

| | Cal | time_diff | Distance(m) |
|---|---|---|---|
| Activity | | | |
| Putaway | Mean | 14.368550 | 47.854105 |
| Putaway | Median | 3.000000 | 46.164325 |
| Putaway | Mode | 2.000000 | 33.914325 |
| Putaway | SD | 47.627938 | 21.459062 |

| | Cal | time_diff | Distance(m) |
|---|---|---|---|
| Activity | | | |
| Replenishment | Mean | 116.359066 | 54.023216 |
| Replenishment | Median | 95.000000 | 54.805934 |
| Replenishment | Mode | 85.000000 | 42.899429 |
| Replenishment | SD | 118.165901 | 23.089940 |

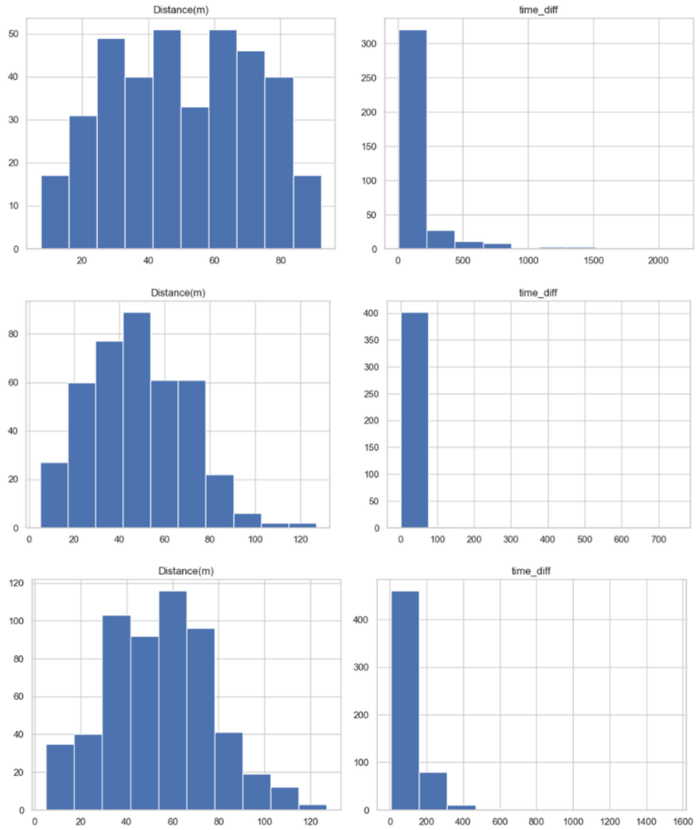


Figure 8 Mean, median, mode, and standard deviation of completed time per pallet (time_diff) and calculated traveling distance per pallet (Distance(m)) (left), calculated traveling distance histogram of each activity (middle), and completed time histogram of each activity (right)

### 4.3 Ranking worker from obtained data

In figure 9 it shows the ranking of worker by time (second) per order (ascending) of each activity. The time (second) per order in Putaway activity shows here is too low. With the higher distance (meters) per order compared to others, the obtained data is suspected that worker scanned to receive and deliver at same spot (not follow normal process). Hence, the result from Putaway activity seems to have low reliability. From the result THANURAKB performed well in all activities even though the distance (meters) per order is higher than some workers, similarly to SIRIRATM and SUPATTAH. This shows that there are factors that affect performance. As work of [6] proposed that picker performance is significantly influenced by work experience, physical fitness, financial reward, training, and welfare. With assumption of same incentive goal, training courses, and welfare from the same company, the factors that influence are to be from work experience and physical fitness.

Picking row#: 31

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 29 | NATTPONT | Picking | 82.579791 | 30.000000 | 2.752660 | 120.000000 |
| 49 | SIRIRATM | Picking | 114.702433 | 41.666667 | 2.752858 | 86.400000 |
| 64 | THANURAKB | Picking | 110.692919 | 47.000000 | 2.355168 | 76.595745 |
| 76 | WIPHAPHONS | Picking | 98.300000 | 50.000000 | 1.966000 | 72.000000 |
| 61 | SUPATTAH | Picking | 105.184940 | 56.000000 | 1.878303 | 64.285714 |

Putaway row#: 26

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 4 | ATHIWATM | Putaway | 109.019687 | 3.0 | 36.339896 | 1200.000000 |
| 26 | NATTAPONC | Putaway | 99.678649 | 3.0 | 33.226216 | 1200.000000 |
| 65 | THANURAKB | Putaway | 85.873858 | 3.5 | 24.535388 | 1028.571429 |
| 15 | KITTIPONGKU | Putaway | 144.364325 | 6.5 | 22.209896 | 553.846154 |
| 9 | KHOMSANY | Putaway | 72.397145 | 9.0 | 8.044127 | 400.000000 |

Replenishment row#: 30

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 63 | SUPATTAH | Replenish | 61.069377 | 25.50 | 2.394878 | 141.176471 |
| 66 | THANURAKB | Replenish | 47.434844 | 42.00 | 1.129401 | 85.714286 |
| 75 | WINAIU | Replenish | 94.697629 | 59.00 | 1.605045 | 61.016949 |
| 2 | ANUPHONS | Replenish | 51.503438 | 88.25 | 0.583608 | 40.793201 |
| 51 | SIRIRATM | Replenish | 68.648858 | 126.00 | 0.544832 | 28.571429 |

Figure 9 Ranking top 5 workers by time (sec) per order (ascending) of each activity as highlighted in red boxes

The result from figure 10 shows that there is no top 5 time (sec) per order worker in this ranking, this indicates that work experience and physical fitness exist and influence worker's performance. KHOMSANY and NATTAPONC are in top 5 in both time (sec) per order and distance (m) per order, so it displays that distance (m) per order affects to the performance in Putaway activity, similar to ANUPHONS in Replenishment activity.

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 32 | PANYAWUTS | Picking | 51.854791 | 115.50 | 0.448959 | 31.168831 |
| 35 | PAYUTP | Picking | 61.863139 | 129.25 | 0.478632 | 27.852998 |
| 85 | WUTICHAIM | Picking | 71.951539 | 412.50 | 0.174428 | 8.727273 |
| 20 | MANOTM | Picking | 75.758788 | 80.00 | 0.946985 | 45.000000 |
| 82 | WIRAYUTC | Picking | 77.027265 | 435.75 | 0.176769 | 8.261618 |

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 56 | SUCHAKRIT | Putaway | 23.679791 | 56.0 | 0.422853 | 64.285714 |
| 86 | WUTICHAIM | Putaway | 40.829791 | 749.0 | 0.054512 | 4.806409 |
| 9 | KHOMSANY | Putaway | 72.397145 | 9.0 | 8.044127 | 400.000000 |
| 65 | THANURAKB | Putaway | 85.873858 | 3.5 | 24.535388 | 1028.571429 |
| 26 | NATTAPONC | Putaway | 99.678649 | 3.0 | 33.226216 | 1200.000000 |

| | Comp.by | Activity | Distance/Count_TO | time/Count_TO | Distance/time | pallet/hr |
|---|---|---|---|---|---|---|
| 31 | NATTPONT | Replenish | 34.400000 | 164.00 | 0.209756 | 21.951220 |
| 16 | KITTIPONGKU | Replenish | 34.400000 | 139.00 | 0.247482 | 25.899281 |
| 66 | THANURAKB | Replenish | 47.434844 | 42.00 | 1.129401 | 85.714286 |
| 2 | ANUPHONS | Replenish | 51.503438 | 88.25 | 0.583608 | 40.793201 |
| 63 | SUPATTAH | Replenish | 61.069377 | 25.50 | 2.394878 | 141.176471 |

Figure 10 Ranking top 5 workers by distance (m) per order (ascending) of each activity as highlighted in red boxes

### 4.4 Worker performance

According to Figure 11-14, workers that fail to meet the company minimum target still do not pass threshold (95%) after calculated with added distance difficulty factor for all activities. This indicates that there are factors other than distance that have a higher influence. It could be work experience, physical fitness or else (e.g. difference of rack level). The result of all activities shows that many workers' performance is lower than the median. Thus, the company may have to reconsider and investigate how the well-performed workers work, then adapt in its standard working process, including set up new company minimum target for worker performance. This will improve overall warehouse performance.

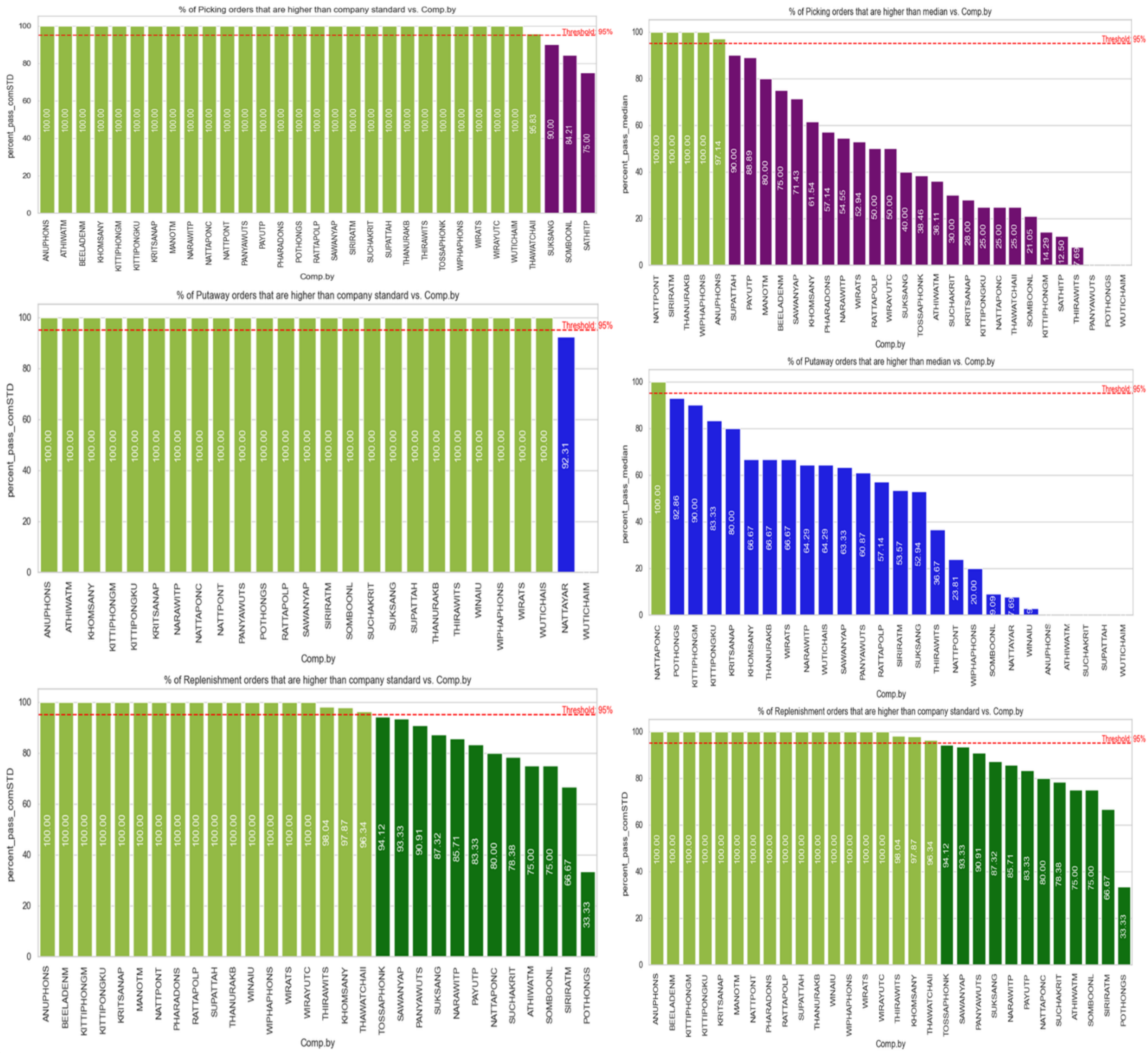


Figure 11 Calculated from our calculation: percentage of each worker and each activity (Picking: top, Putaway: middle, Replenishment: bottom) that the completed orders are higher than company minimum target (left) and median (right)


Figure 12 Using added distance difficulty factor calculation (0.5, 1, 1.5: top, 0.25, 1, 1.75: middle, 075, 1, 1.25: bottom): percentage of each worker in Picking activity that the completed orders are higher than company minimum target (left) and median (right)

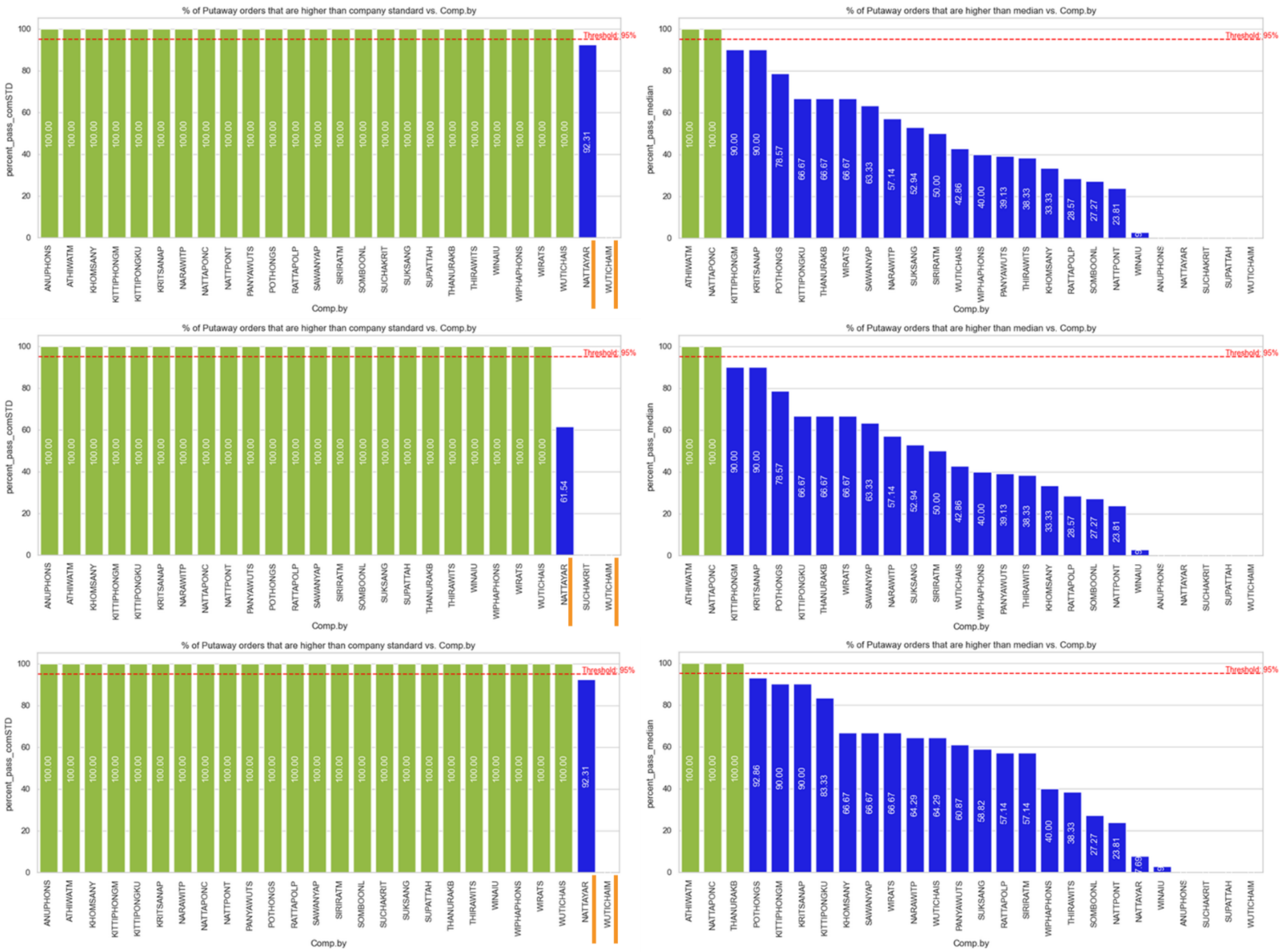


Figure 13 Using added distance difficulty factor calculation (0.5, 1, 1.5: top, 0.25, 1, 1.75: middle, 075, 1, 1.25: bottom): percentage of each worker in Putaway activity that the completed orders are higher than company minimum target (left) and median (right)

Figure 14 Using added distance difficulty factor calculation (0.5, 1, 1.5: top, 0.25, 1, 1.75: middle, 075, 1, 1.25: bottom): percentage of each worker in Replenishment activity that the completed orders are higher than company minimum target (left) and median (right)

## 5. Conclusion and Future Work

For performance bias mitigation, before we pay attention to the performance calculation. Firstly, it is imperative to revisit the underlying cause which is the balance of task assignment as the data shows that there is no balance of order amount assigned to workers and distance per order of each activity. Secondly, algorithms to guide worker by suggesting the potential shortest path should be applied avoiding nonexperience worker to spend non-value-added time, improving performance not only for worker but also the whole warehouse. Thirdly, we should ensure the data reliability about time utilization of each order especially in this work in Putaway activity. As the data showed, and lead to suspect that there are some workers who did not follow normal working procedure. This will highly affect the analysis and importantly the performance calculation. By adding the distance difficulty factor, there are many workers that fail to meet the threshold (95%) compared to company minimum target in all activities. This indicates that traveling distance affects performance and adding the distance difficulty factor will mitigate the exiting bias in calculation. Selecting the distance difficulty factor value for implementation, the company may begin with 0.50, 1.00, 1.50 for short, medium, and long distance respectively, and evaluate worker feedback to find the suitable value.

To further study it is recommended to expand to analyze data other than this work focused area, consider Z axis (rack level) for productivity calculation, apply multiple actual I/O points including cross aisle to shortest path algorithm, and gather more data adding other factors that affect productivity in calculation. The absence of precise path data within WMS can impose limitations on understanding the intricate movements and activities of workers within a facility. Adopting technologies like Real-Time Location Systems (RTLS) can enhance the reliability of data collection and analysis in warehouse.

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