IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 30 October 2023, accepted 3 December 2023, date of publication 8 December 2023, date of current version 15 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3341396

RESEARCH ARTICLE

A Study of the Man and Unmanned Teaming System for Improving Efficiency in a Fulfillment Center

AZIMBEK KHUDOYBERDIEV, SHUBHANGI S. R. GARNAIK, HA YOUNG KIM, AND JIHOON RYOO
Department of Computer Science, The State University of New York, Korea (SUNY Korea), Incheon 21985, South Korea

Corresponding author: Jihoon Ryoo (jihoon.ryoo@stonybrook.edu)

This work was supported in part by the Korean National Research Foundation under Grant NRF-2021R1F1A1052489; in part by the Ministry of Science and ICT (MSIT), ICT Consilience Creative (ICT CC) Program, under Grant IITP-2019-2011-1-00783/ICT Start-Up Fund under Grant RS-2022-00156555; in part by the Ministry of Land, Infrastructure, and Transport (MOLIT) Start-Up Fund under Grant RS-2022-00144171; and in part by the Korea Radio Promotion Association (RAPA) Extended Reality Lab (XR-LAB) Grant.

ABSTRACT In fulfillment centers, efficient inbound transportation and goods storage are crucial factors that impact overall performance and supply chain costs. Traditional processes often involve human workers performing repetitive tasks, leading to increased expenses. This study presents a Manned-Unmanned Teaming (MUM-T) approach that combines unmanned Automated Guided Vehicles (AGVs) with manned forklift vehicles to automate these processes and minimize costs. The primary objectives are to model AGV-based unmanned inbound transportation, design a manned traveling forklift problem (TFP) with a shortest path algorithm, and compare the MUM-T approach to traditional methods in terms of distance, time, and cost. Results from theoretical analysis and simulations show that the MUM-T approach can reduce traveling distance, working hours, and operational costs by up to 32%, 38%, and 51%, respectively. Moreover, the proposed algorithm enables *Beginner* and *Intermediate*-level forklift operators to achieve efficiency comparable to that of *Professionals*. These findings indicate that implementing the MUM-T approach can significantly enhance the efficiency and cost-effectiveness of inbound transportation and forklift processes in fulfillment centers.

INDEX TERMS Automated guided vehicles, fulfillment center, improving efficiency, inbound transportation, man and unmanned teaming, process automation, traveling forklift problem.

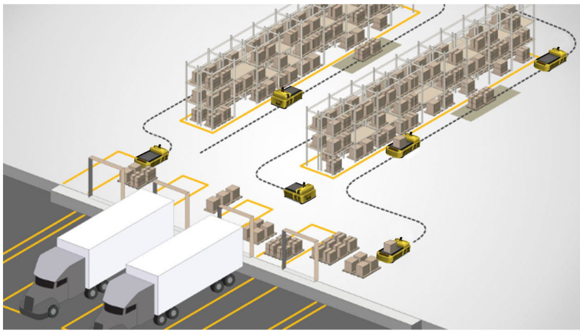
I. INTRODUCTION

As e-commerce continues to grow, so does the demand for faster and more efficient fulfillment processes. In addition to the logistical and administrative processes mentioned [1], fulfillment centers also face challenges such as labor shortages, order accuracy, and reducing delivery times. To address these challenges, many companies are exploring new technologies such as automation, robotics, and artificial intelligence. These technologies are being used to automate repetitive tasks, optimize inventory management, and improve order picking and packing processes. Yet, as it stands, over 80% of fulfillment centers predominantly rely on a human workforce. A mere 15% have adopted mechanized systems, while only 5% have integrated advanced automation equipment and solutions [2].

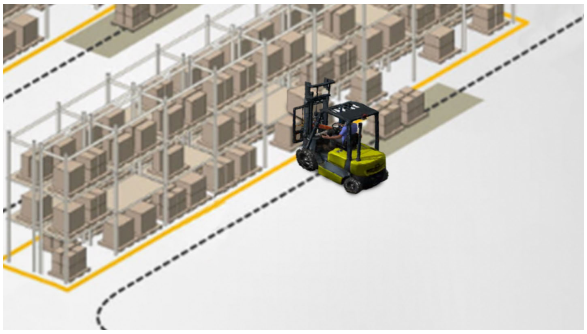
E-commerce fulfillment centers play a critical role in the success of e-commerce businesses. Effective management of these centers is essential for meeting customer demands, reducing costs, and maintaining a competitive edge [3], [4], [5]. As the industry continues to evolve, companies must adapt to new technologies and processes to improve efficiency and meet customer expectations.

In recent decades, many processes in fulfillment centers have been managed manually. Indeed, the human workforce has been thought to have several advantages over automated systems, as detailed by Fragapane et al. [6]. These advantages include:

The associate editor coordinating the review of this manuscript and approving it for publication was Claudio Loconsole.



(a) Repetitive and menial delivery tasks for AGVs



(b) Complex and skill-needed forklift tasks for human

FIGURE 1. System view of MUM-T.

1) **Reliability**: Human workers can handle a wide variety of tasks with minimal errors and can adapt to changing conditions more effectively than machines. This makes them a reliable resource in fulfillment centers where diverse tasks and products are managed.
2) **Efficiency in handling and picking diverse products**: Human workers can recognize, handle, and pick different types of products, even those that are not easily identified or managed by automated systems.
3) **Swift decision-making**: Human workers can make quick decisions based on their experiences, knowledge, and judgment. This ability to think on their feet and respond to unexpected situations allows them to maintain smooth operations in fulfillment centers, even during periods of high demand or workload fluctuations.
4) **Adaptability to workload fluctuations**: Human workers can adjust their workspace and effort to meet the demands of high sales seasons or other periods of increased workload.

With the growing volume of goods, increased consumer expectations, and tighter delivery windows, there's a pressing need for efficiency improvements. A major bottleneck has been the traditional reliance on human workers for repetitive and mundane tasks, leading to inefficiencies and higher operational costs [7]. While humans are incredibly adaptable and capable of handling complex tasks, repetitive and predictable processes often lead to errors, fatigue, and inefficiencies [8].

The introduction of automated guided vehicles (AGV) and autonomous mobile robots (AMR) in various industries has already shown potential in enhancing operational efficiency [9], [10]. These unmanned systems follow predetermined paths with precision, minimizing errors, and maximizing throughput. However, to achieve a significant leap in efficiency, it's essential to envision a system where humans and machines collaboratively work, each maximizing its unique strengths.

The synergy between manned and unmanned systems could unlock new levels of cost savings and efficiency in fulfillment center operations. The goods storing process is one of the time-consuming and costly operations, and it can contribute 40%-50% of the total fulfillment center operating cost [11]. Improving this process can significantly decrease the expenses for businesses. In this process, daily received items from various sources and suppliers must be stored into the facility until they receive orders from customers. This process largely involves two main tasks: *inbound transportation* and *forklift* processes.

Inbound transportation entails the transportation of goods from the receiving docks to their designated storage spots. This routine and repetitive task often involves traveling considerable distances daily. While in the *forklift* process, goods are lifted from the facility floor and placed in assigned racks using forklift trucks. This task is complex and requires skilled human operators. In both processes, human workers may experience fatigue, leading to sub-optimal traveling path choices around storage racks, potentially impacting productivity and resulting in financial inefficiencies [12].

This work proposes a Manned and Unmanned Teaming (MUM-T) approach that aims to harmoniously blend human-operated forklifts and unmanned AGVs to improve efficiency in fulfillment centers (Fig. 1). We introduce the traveling forklifter problem (TFP) and AGV-based inbound transportation algorithms to optimize traveling time and distance of manned forklift operators and unmanned AGVs, respectively. In AGV-based inbound transportation, AGVs perform the point-to-point delivery of items from the main queue to the assigned queues by following pre-determined shortest paths. While in the TFP, the modified nearest neighbors algorithm guides human forklift operators to complete their task by following the optimal traveling distance. The design and algorithms of the proposed MUM-T system are simulated and tested in various scenarios using Coupang's Warehouse dataset. We also empirically assess the efficiency of our approach against conventional methods by simulating various operational scenarios based on operator experience levels.

The remainder of this paper is structured as follows: Section II presents the literature review, Section III details the methodological approach, Section IV discusses the simulation of the proposed approach, Section V examines various human-machine interaction scenarios and their effects on time and cost, Section VI compares the results based on the scenarios discussed. Finally, Section VII concludes the paper, highlighting theoretical implications, limitations, and future research directions.

II. LITERATURE REVIEW

The trend of using AGVs is on the rise due to the current issues faced by fulfillment centers, such as a lack of skilled workers, high labor expenses, and the need for 24/7 operations. Additionally, the decrease in cost has made AGVs a practical alternative to human and manual methods for transporting pallets within a warehouse and loading/unloading palletized vehicles. Global companies have been investing billions of dollars to create smarter fulfillment centers by widely deploying AGVs, Artificial Intelligence (AI), and the Internet of Things (IoT) technologies.

For instance, the Alibaba group constructed a smart e-commerce fulfillment center to support online shopping in the Beijing-Tianjin-Hebei megalopolis in 2014 [13]. Over 500 AGV robots and AI have been widely deployed in the fulfillment center to handle daily 150, 000 orders by providing same-day or next-day delivery. AGVs are used for inbound delivery by following optimal paths and decreasing human power and traveling distance, while AI is deployed for sales forecasting, robot scheduling, and route planning. Therefore, the manpower is reduced by up to 70% and the overall efficiency is increased by up to 40%.

The other global company, Amazon, has been managing its orders and maintenance of warehouse goods by completely automating its fulfillment center for over a decade now [14]. They aim to make work safer and more productive. Toward this revolution, Amazon deployed over 520, 000 mobile robot drive units across numerous fulfillment centers. These robots perform lifting and placing heavy items in a rack by using Cardinal AGVs which are equipped with advanced AI and computer vision. Amazon has slashed operating costs by 22% by deploying robots, the transition on a great scale could lead to a massive saving of about 2.5 billion.

Many researches have been conducted to improve the efficiency and minimize costs in fulfillment centers by optimizing goods storing [15], order picking [16], [17], batching sequencing [18], [19], goods loading [20] and so on.

This work represents an iterated local search algorithm to solve order batching, batch sequencing, picker assignment, and routing problems in warehouse management based on industrial information integration (IIT) [18]. Hybrid iterated local search algorithms embedded with heuristic rules provide an effective and efficient scheduling method by solving batching, assignment, sequencing, and routing problems. Li et al. introduces a heuristic ant colony algorithm to automate AGV operations with path optimization [21]. An improved ant colony algorithm that overcomes the shortcomings of the traditional method, avoiding local optimal issues and providing a more efficient route. It extends from two-dimensional planning to optimizing paths in a three-dimensional warehouse space. By converting distances into horizontal and vertical lines, the algorithm optimizes the AGV's path through multi-row three-dimensional shelving.

The study [17] provides an optimized storage policy known as scattered-correlation storage policy based on the commodity classification (SCSPCC) by taking into account commodity classification, commodity storage, and consumer demand pattern. It is designed to enhance client satisfaction and lower warehouse operating expenses. This approach is only viable if a significant number of customers consistently purchase related products. However, if buying patterns become erratic then this solution may lose its effectiveness and relevance.

A two-stage hybrid heuristic algorithm (TS-HHA) [19] aims to decrease the number of trips made by the robot to fulfill a request. Using dynamic programming and an adaptive neighborhood search algorithm with a constructive heuristic algorithm, the two stages of reducing and assigning help to locate a crucial rack set, which can focus attention on the most promising racks and accelerate problem-solving to provide high-quality simultaneous assignment schemes. However, a robotic mobile fulfillment system observes high calculation time.

Autonomous aerial robots are popular in some warehouses and manufacturing centers. Its agile navigation and faster processes encouraged owners to use them to automate manufacturing warehouses [22]. While unmanned aerial vehicles are functional, they present notable issues. Safety remains a primary concern due to the risk of objects dropping. Given the uniform appearance of warehouse racks, robots often struggle to locate specific items.

Industrial Internet of Things (IIoT) based warehouse automation systems have been proposed in the past as an effective management approach [23]. These IIoT-based robotic warehouse systems are used to manage goods and autonomous robots and, in turn, increase the competitiveness of logistics companies. Despite the benefits, various downsides are observed. IIoT-driven systems have weak security and privacy configurations, therefore they can be hacked by various network attacks [24], [25].

Above mentioned and many other existing studies described in the literature [26], [27], [28] have primarily focused on boosting overall efficiency by refining warehouse processes or by implementing AGVs with optimized paths. In our work, seeking solutions beyond traditional practices, we present the concept of MUM-T, efficient teaming of automated robots like AGVs and human-driven forklifts. AGVs perform mundane and repetitive inbound transportation tasks, while human-driven forklifts are employed to optimize the loading process of items onto designated storage racks.

III. DATA ANALYSIS AND PROBLEM STATEMENT

A. DATA COLLECTION AND ANALYSIS

We focus on the Coupang's Warehouse located in Incheon, South Korea [29], [30]. This warehouse serves as an e-commerce fulfillment center for the Coupang e-commerce platform, selling a wide range of products, such as household products, fashion, beverages, food, and beauty products by

TABLE 1. Performance (boxes/hour) and velocity (m/s) of operators.

Working Level	Transporter		Forklift	
	performance	velocity	performance	velocity
Beginner	20-24	0.6-0.8	35-40	0.6-0.8
Intermediate	26-30	0.8-1.0	41-46	0.8-1.0
Professional	32-36	1.0-1.2	47-52	1.0-1.2

international and local brands. The fulfillment center has facilitated exponential benefits for customers by providing same-day, dawn, and rocket fresh delivery options.

We collected data in two main phases. First, we gathered information on process participants from Coupang's fulfillment center and a variety of secondary media sources, including company websites and online articles. In the second phase, we delved into CCTV recordings and surveyed employee performance in the goods storing processes. Additionally, to ensure the integrity of the collected data, managers were interviewed for validation. Afterward, data underwent a refinement process to address outliers and inconsistencies, preparing it for the simulation model.

Several participants (actors and objects) are involved in the goods storing process in fulfillment centers. We explain the role of participants used to build our proposed MUM-T model in detail as follows:

- *Main Queue*-goods that first enter the warehouse are placed here temporarily until they are sent to each rack's queues by the Transporter.
- *Transporter operator*-performs inbound transportation and distributes received goods from the main queue zone to each rack's queue zone.
- *Forklift operator*-lifts the goods located on the floor of each rack's queue zones to their assigned racks.
- *Racks*-store huge amounts of items until receiving orders from customers.
- *Rack Queues*- each rack has an empty area adjacent to it to temporarily place the goods on the floor until they are lifted to assigned racks by the forklift.
- *Automated Guided Vehicle (AGV)*-transports items from the main queue to each rack's queue by following optimal predetermined pathways.

The proficiency levels of human operators can vary according to their years of experience, efficiency in tasks, and overall performance. Therefore, transporter and forklift operators' working levels are categorized as *Beginner*, *Intermediate*, and *Professional* in the fulfillment center. Beginner and Intermediate level workers have limited and moderate amounts of experience, respectively. Whereas, a Professional has a high level of knowledge and experience in transportation and forklift processes.

In addressing the performance disparities between expert and non-expert operators in inbound transportation, it is crucial to consider various factors beyond just knowledge of navigation plans or forklift operation skills. Non-expert

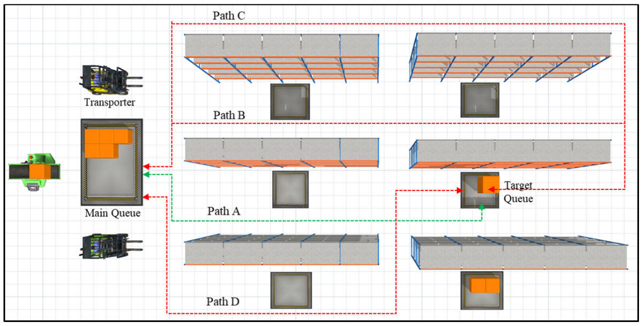


FIGURE 2. Random path selection challenge in inbound transportation.

operators may have a basic understanding of the navigation plan and the warehouse layout, but they often lack the advanced skills needed to anticipate potential obstacles, optimize routes in real time, and handle the forklift efficiently under varying warehouse conditions. Moreover, even experienced operators can experience a decline in performance due to the monotony of repetitive tasks, leading to fatigue. Therefore, an optimized forklift process is necessary to provide a standardized path and set of visiting nodes for operators of all skill levels.

Table 1 represents the hourly performance and velocity of the transporter and forklift operators in boxes per hour (b/h) and meters per second (m/s), respectively based on the proficiency level of operators. As can be seen, beginner, intermediate, or professional-level transporters deliver 20-24, 26-30, and 32-36 boxes per hour, respectively, from the main queue to each rack queue. Whereas the delivered boxes are stacked on each rack by beginner, intermediate, or professional-level forklift operators. Their hourly boxes' stacking performance is 35-40, 41-46, and 47-52 boxes per hour, respectively. However, the same velocity ranges can be observed in the transporter and forklift operators. Beginner, Intermediate, and Professional operators' velocity range from 0.6-0.8 m/s, 0.8-1.0 m/s, and 1.0-1.2 m/s respectively.

B. THE PROBLEM STATEMENTS

1) CHALLENGES IN INBOUND TRANSPORTATION

Human transporters must perform inbound delivery by moving items from the main queue to each rack queue, which is a repetitive and menial task. This task usually requires traveling many miles a day and as a result, human workers lose productivity by feeling tired, being more distracted while carrying items, and choosing pathways randomly to deliver the items.

Consider the following example as shown in Fig. 2, to effectively represent the challenge of a Transporter. The primary task of a human transporter is to deliver boxes from the main queue to the target queue. To accomplish this task, there are several paths (A, B, C, D) available. Human transporters can choose any of them randomly, however, Path A is the shortest and most optimal path to travel between the main and target queue among available paths. Moreover,

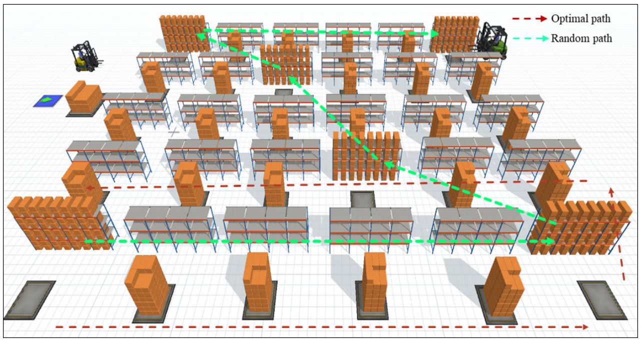


FIGURE 3. Random path selection challenge in item forklift.

human transporters can choose path A to deliver the item but can choose the longest path C to return to the main queue. When a human transporter selects a random path, it adds to the waste of time, energy, and money for the fulfillment center. This problem can be accumulated and amplified in a large fulfillment center, which can contain hundreds of racks.

The results of data analysis show that the beginner-level transporter chooses the sub-optimal paths 5-6 times out of ten, due to poor experience, feeling tired, or various other distractions. Whereas, the intermediate and professional level transporters follow sub-optimum paths 3-4 and 0.5-1 times out of 10, respectively. As a result, their final overall performance, the number of boxes they delivered, and traveling distance are different in the transportation process. Therefore, we introduce point-to-point delivery using AGVs to optimize and automate the item transportation process. A detailed description has been given in Section IV-A.

2) CHALLENGES IN ITEM FORKLIFT PROCESS

The forklift process starts after or during the inbound transportation process. The forklift drivers or operators' primary responsibility is to load and unload received items to and from the rack while trying to optimize the loading paths to ensure operational efficiency and avoid damage to vehicles.

According to proficiency level, experience, or personal behavior, the operators might choose a different path to complete the overall forklift process. Even if the operator has remarkable personal experience, repetitive tasks might bring fatigue and less productivity and, as a result, forklift operators might choose sub-optimum paths to complete the work.

One of the worst-case scenarios in the forklift process is represented in Fig. 3. The forklift driver has selected random racks to fill and moves from rack to rack without following an optimal path. This results in a waste of time and energy for the company, because for each extra working hour, the driver has to be paid. In addition, the queued items wait longer to be stacked on the racks.

The above-mentioned random path selection and the traveling problem can be described as *Traveling Fork-Lifter Problem (TFP)*. To solve TFP, the forklift operator should traverse the most optimal path around the fulfillment center. The traveling fork-lifter problem answers the following question: from a given arrangement of queues and distances between each pair of queues, what is the shortest possible route the forklift driver can follow so that it visits each queue exactly once, without the need to return to the starting point after visiting all queues? By solving the TFP problem, we can provide the most optimal and accurate map to achieve the shortest path and time to complete the forklift process.

IV. PROPOSED MUM-T APPROACH

After analyzing challenges in inbound transportation and item forklift processes, we propose the MUM-T approach to solve both inbound transportation and item forklift issues. Fig. 4 represents a high-level overview of reconstructing the traditional goods-storing process with the proposed MUM-T-based approach. As can be seen, the traditional human-assisted goods storing process is divided into two sub-processes in the proposed approach, namely, AGV-based point-point inbound delivery and traveling fork-lifter problems.

AGV-based point-to-point inbound delivery is introduced to optimize the traveling time and distance of human transporters who navigate the storage center to transport boxes from the main queue to all specific rack queues. Once the rack queues are filled with boxes, the human-operated forklift can navigate to each of the rack queues using the optimal shortest path to stack those boxes onto the respective racks. This decreases the overall traveling time and distance as compared to the time required for the traditional random path selection approach.

A. AGV-BASED OPTIMAL INBOUND TRANSPORTATION

The overall traveling distance and time are different among the three different working levels. According to the CCTV videos and survey data, professional and intermediate-level transporter drivers are experienced enough to navigate via the optimal route, while, beginner-level drivers may find it difficult to navigate around a larger fulfillment center and hence have a higher chance of choosing non-optimal routes. The overall traveling distance for AGV and human transporters can be calculated using the following equation.

$$D_{A,B,I,P} = \sum_{Q=0}^{Q} (M \times N \times 2 + \alpha \times D) \tag{1}$$

where $D_{A,B,I,P}$ presents the overall traveling distance for AGVs, beginner, intermediate, and professional level transporters. Q presents the number of queues, N is the number of boxes required for each queue, whereas M represents the distance between the main queue and each of the specific rack queues. Multiplying with 2, accounts calculate the going and coming back distance from the main queue to the specific queue. α represents the inefficiency weights of the human transporters, and their values lie between 0 and 1, which implies that a professional driver has the lowest inefficiency weights (0-0.1), while intermediate

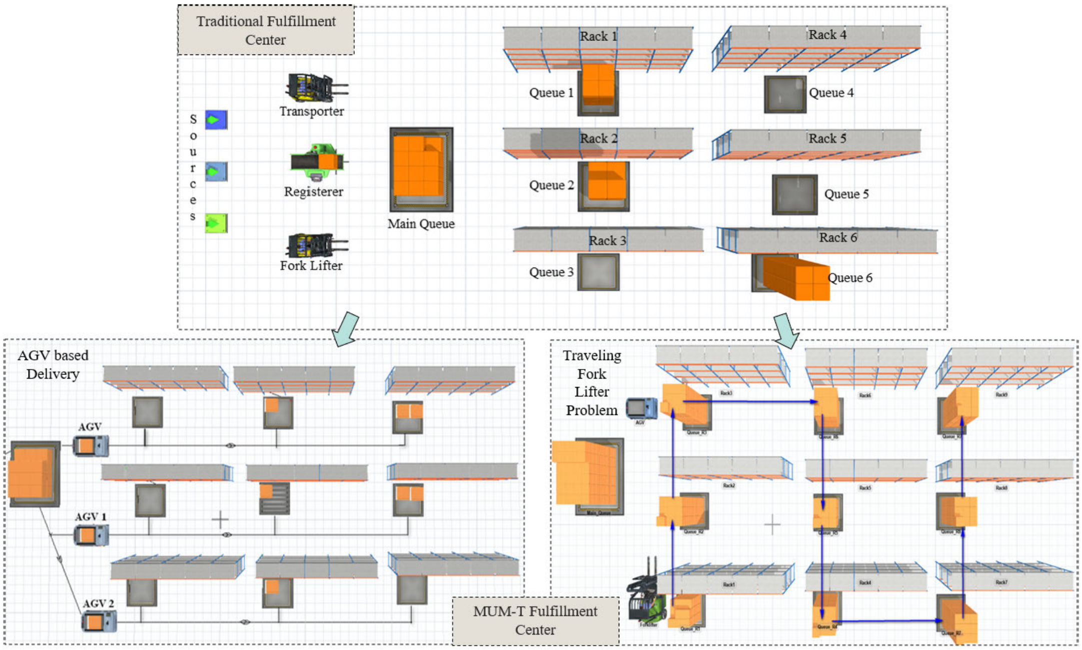


FIGURE 4. Overview of the proposed MUM-T-based fulfillment center.

and beginner level transporters have (0.1-0.2) and (0.2-0.3) inefficiency weights respectively. This inefficiency weight parameter has been extracted from the historical overall performance data based on different levels of workers.

The calculation of the traveling time is quite straightforward. Based on the traveling distance required to fill all of the queues and the traveling speed of the transporter and AGVs, the required time to complete all point-to-point deliveries can be computed with (2).

$$T_{A,B,I,P} = \frac{D_{A,B,I,P}}{V_{A,B,I,P}} \tag{2}$$

where T presents the required overall time to deliver the required items for each queue for AGV, beginner, intermediate, and professional-level drivers. D is the overall traveling distance for each actor and V is the velocity (speed) of the actors. Based on the above equations, we can compute the point-to-point traveling distance and required time for human-assisted Transporter and AGVs using Algorithm 1.

B. TRAVELING FORK LIFTER PROBLEM (TFP)

The TFP is the name coined in this paper as the traveling salesman problem (TSP) [31] whose objective is to find the shortest travel path of the forklift. The difference to the TSP is that the forklift does not return to the starting point. We introduce a modified nearest neighbors algorithm to solve the TFP. Given a set of nodes for the forklift to travel to, the algorithm features a user-specified probability of selecting a random node instead of its nearest neighbor. This feature simulates real-world situations where a less experienced forklift driver may often choose a longer route because they are not familiar with the optimal path. Furthermore,

Algorithm 1 The AGV-Based Optimal Inbound Transportation Algorithm

Require: Q, N, M, α, D, V
Ensure: $D_{A,B,I,P}$, $T_{A,B,I,P}$
Initialize $D_{A,B,I,P} = 0$
for $q = 0$ to Q **do**
  $D_{A,B,I,P} \leftarrow D_{A,B,I,P} + (M[q] \times N \times 2 + \alpha \times D)$ ▷ Eq. 1
end for
$T_{A,B,I,P} \leftarrow \frac{D_{A,B,I,P}}{V}$ ▷ Eq. 2
return $D_{A,B,I,P}$, $T_{A,B,I,P}$

experienced operators are well-acquainted with warehouse infrastructure and typically choose the shortest routes to the next queue. Therefore, the purpose of this algorithm is twofold: first, to simulate travel routes for operators with various skill levels. Secondly, to compute the most optimal routes using the nearest neighbors algorithm.

By contrasting the optimal path with the simulated route, we can identify the potential improvements a driver could achieve by adhering to the nearest neighbors method. By following this optimal path, less experienced drivers not only reduce travel distance and time but can also achieve the same level of efficiency as professional forklift drivers, without requiring extensive training.

In the forklifting process, the forklift moves from one "assigned queue" to another to load items in each queue to its corresponding rack. To clarify the meaning of "assigned queues", only the assigned queues contain the items the forklift needs to load, while unassigned queues in the warehouse are empty and are thus not visited. In this process, the overall forklift working time can be divided into two parts: the total time required to move between queues, known as the travel time, and the time required to load items in all the assigned queues to their respective racks, known as the loading time. This is shown in the following equation:

$$T = T_l + T_d \tag{3}$$

where T is the total forklift operating time, T_l is the loading time, and T_d the travel time. The overall forklift loading time can then be calculated using the following equation:

$$T_l = \sum_{i=0}^{Q} (t \times N_i) \tag{4}$$

where T_l is the total forklift loading time, Q is the number of assigned queues, t is the average time spent loading one item to a rack, and N_i is the number of boxes to load for queue i.

To calculate the total travel time T_d, the total distance required to move between queues or travel distance has to be evaluated first. This is defined by the following equation:

$$T_d = \frac{D_f}{v_f} = \frac{\sum_{i=0}^{Q-2} d(p_i, p_{i+1})}{v_f} \tag{5}$$

where D_f is the total travel distance, v_f is the fixed forklift travel speed, Q is the number of assigned queues to travel to, and $d(p_i, p_{i+1})$ is the Manhattan distance between queues i and $i+1$, which is defined by the following equation:

$$d(p_1, p_2) = |n \times \delta x| + |m \times \delta y| = |x_2 - x_1| + |y_2 - y_1| \tag{6}$$

where δx is the horizontal distance between neighboring queues, δy is the distance between neighboring rows, n is the number of queues the nodes are apart horizontally and m is the number of rows the nodes are apart vertically.

The traveling forklift problem therefore attempts to minimize $d(p_i, p_{i+1})$ between each i and $i+1$ queue and, as a result, optimizes travel time T_d, while loading time T_l is a problem to consider separately. The problem lies with inexperienced forklift drivers choosing sub-optimal paths and to compare the difference in performance between the three different skill levels, the first task is to simulate the paths taken by all three levels. This is done by implementing an algorithm such that, given a starting node, it repeatedly selects an unvisited node to travel to from the current node until all nodes are visited.

The algorithm represents the overall set of assigned queues of the warehouse as an undirected, weighted, complete graph where each queue with items waiting to be loaded into the racks is a node and an edge is the Manhattan distance between any two queues. Note that all the nodes are connected to every other node to form a complete graph and this is done so that the path-finding algorithm has the option to freely select any unvisited node to reach the next. The pseudo-code for the path-finding algorithm is shown in Algorithm 2. Detailed explanations for the algorithm complexity and analysis are shown in Section IV-C.

Algorithm 2 The Path Finding Algorithm for the Traveling Forklifter Problem

Require: *Nodes* ▷ List of all nodes to visit
Require: $\beta \in [0, 1]$ ▷ Probability of choosing nearest node instead of a random node
Require: i_o ▷ The starting node
1: Initialize empty list *path*
2: $i \leftarrow i_o$
3: **repeat**
4:     Append i to *path*
5:     $r \leftarrow$ random real number $\in [0, 1]$
6:     **if** $r \leq \beta$ **then**
7:         **for** each j in *Nodes* and not in *path* **do**
8:             Compute $d(i, j)$
9:         **end for**
10:         $j* \leftarrow argmin\, j\, (d(i, j))$ ▷ Simply choose the nearest neighbor j from the current point i.
11:     **else**
12:         $j* \leftarrow$ random node not in *path*.
13:     **end if**
14:     $i \leftarrow j*$
15: **until** all nodes in *Nodes* also in *path*

As shown in Algorithm 2, the user has to input a real number β that ranges from 0-1, which represents the probability that the pathfinding algorithm will choose the next nearest unvisited node with respect to *current* instead of choosing a random unvisited node as its next point. The starting node is also selected by the user and from there, the algorithm repeatedly chooses the next point not yet in *path* until all assigned nodes are visited. After all nodes are in *path*, the entire sequence of nodes in the appended order can then be defined as one travel path. As the distances between all subsequent nodes in *path* are known, Eq. 5 can then be used to find the travel distance D_f, which is finally divided by v_f to obtain the travel time.

The difference in driver proficiency levels is solely represented by the β value in step 1. This ratio is manually set by the user before running the algorithm and a number closer to one indicates a higher skill level. For each decision on which node to visit next, a professional driver has a higher probability (set within the range of 0.9-1) of selecting an optimal node compared to a beginner (0.3-0.5) and an intermediate (0.5-0.8) driver. For a fair and direct comparison, the starting queue is the same for all skill levels.

In this case, the optimal node choice is the current node i's nearest neighbor. Although the nearest neighbor is a greedy algorithm that selects the local optimum without considering the global minimum, it accomplishes the goal of reducing the traveling distance compared to a totally random path selection.

C. COMPLEXITY ANALYSIS OF PROPOSED ALGORITHMS

The complexity of Algorithm 1 is as follows. The algorithm begins with the initialization of $D_{A,B,I,P} = 0$, and this initialization step is executed in constant time, denoted as $O(1)$. The AGVs must deliver all items for the assigned queues in a total of (Q) times, therefore there is a loop structured as *for* $q = 0$ *to* Q. Within this loop, the operation Eq. 1 is carried out. Each of these operations, regardless of the values, executes in constant time. Thus, the time complexity for this part is also $O(1)$. The algorithm only uses a constant amount of additional space regardless of the input size. Considering the entire algorithm, with the loop running Q times and each iteration having a constant time complexity, the cumulative time and space complexity of the AGV-based optimal inbound transportation algorithm is $O(Q)$ and $O(1)$, respectively.

The TFP algorithm is divided into two major segments. Firstly, before running the algorithm, the user-defined parameters, a pre-arranged set of assigned queues, and an adjacency matrix are initialized to efficiently determine the distance between any pair of nodes. Secondly, for each skill level (beginner, intermediate, and professional), the TFP algorithm generates m paths to compute the average travel distances. For generating a single path, the function *nearestPlusRandom()* representing the entire Algorithm 2, determines the order of all points from the prearranged set and returns the sequence. Inside *nearestPlusRandom()* contains two sub-functions, *chooseNearest()* and *chooseRandom()*, to perform the next node selection on a path.

For the first part, for each skill level lvl and a prearranged set of n points $Q_n = \{p_0, p_1, \ldots, p_n\}$ the forklift has to travel to, the user has to specify the number of paths m to generate, β_{lvl} from Algorithm 2, the forklift speed $v_{f,lvl}$ from Eq.5, and the average time spent for loading one item to a rack t_{lvl} from Eq.4. After initializing Q_n, a $n \times n$ adjacency matrix A is created to list the distances between any two points, where accessing the *ith* row and *jth* column of A returns the Manhattan distance between points i and j. With a total of n^2 elements to compute distance in A and the Manhattan distance calculation taking $O(1)$ time, the time and space complexity to initialize the adjacency matrices are both $O(n^2)$.

For the second part, a function *nearestPlusRandom()* is called that returns a generated list of *Point* objects $Q_{n,lvl,i}$, which is a sequence of n ordered points representing a single forklift travel path. Inside the function, either *chooseNearest()* will be called with probability β_{lvl} or *chooseRandom()* otherwise. The time complexity of using either function is $O(n)$, as *chooseNearest()* traverses through the *ith* row of the adjacency matrix A to find p_i's nearest neighbor and *chooseRandom()* traverses through *unvisited*, a list of n or less unvisited points, to find and remove the visited point. With n points total to choose from, the time complexity of *nearestPlusRandom()* is therefore $n \times O(n) = O(n^2)$ while the space complexity is $O(n)$ from returning $Q_{n,lvl,i}$ containing n $O(1)$ points. Repeating m times, the total time and space complexities are therefore $O(mn^2)$ and $O(mn)$, respectively.

After computing average travel distances for all skill levels, a separate code calculates the travel and box unloading times using user-defined parameters. These time calculations are straightforward and all done in $O(1)$ time and space. To sum up, the overall worst/best/average case time complexity of the TFP algorithm is $O(mn^2)$ while space complexity is either $O(n^2)$ if $n > m$ or $O(mn)$ otherwise.

TABLE 2. Simulation model and system components.

Simulation components	System components
Fixed resources	Source, main queue, sub-queue, rack
Vehicles	Transporter, forklift, AGV
Parameters	Rack size, number of racks, capacity
Events	Queuing, transportation, stacking, etc
Inputs	Velocity, distance, processing time, etc
Outputs	Traveling distance, time, efficiency

V. SIMULATION AND SCENARIOS

A. MODEL SIMULATION

The traditional (baseline) and proposed MUM-T models were developed using a FlexSim ® simulation software. The FlexSim is an object-oriented software environment that allows to develop, model, simulate, visualize, and analyze dynamic-flow processes in various systems, including, warehousing, healthcare, material handling, manufacturing and just to name a few [32].

To generate a visually realistic simulation model, Coupang's e-commerce fulfillment center's overview was deeply analyzed to trace the required components to simulate the proposed system. The simulation model and proposed system components are summarized in Table 2. The simulator software allowed us to deploy the logic, and input the rack size, vehicle speed, rack capacity, number of racks, the distance between the main queue and the racks' queue, processing time, and other parameters. Those parameters were carefully chosen in the model development. However, these parameters can be easily adjusted, allowing for the simulation model to be scaled over various industries and fulfillment centers. Based on event types and various input parameters, the developed model provided the output values in terms of traveling distance and time and operational efficiency for both baselines and proposed approaches.

To further illustrate the feasibility of the proposed MUM-T approach and algorithm in actual fulfillment centers, Coupang's fulfillment center plan has been simulated for the case analysis. The simulated storage plan is presented in Fig. 5. The storage is divided into two main areas: the main queue area and the storage area. The received items from various sources are kept in the main queue until they are delivered to specific racks to store. Transporter operators

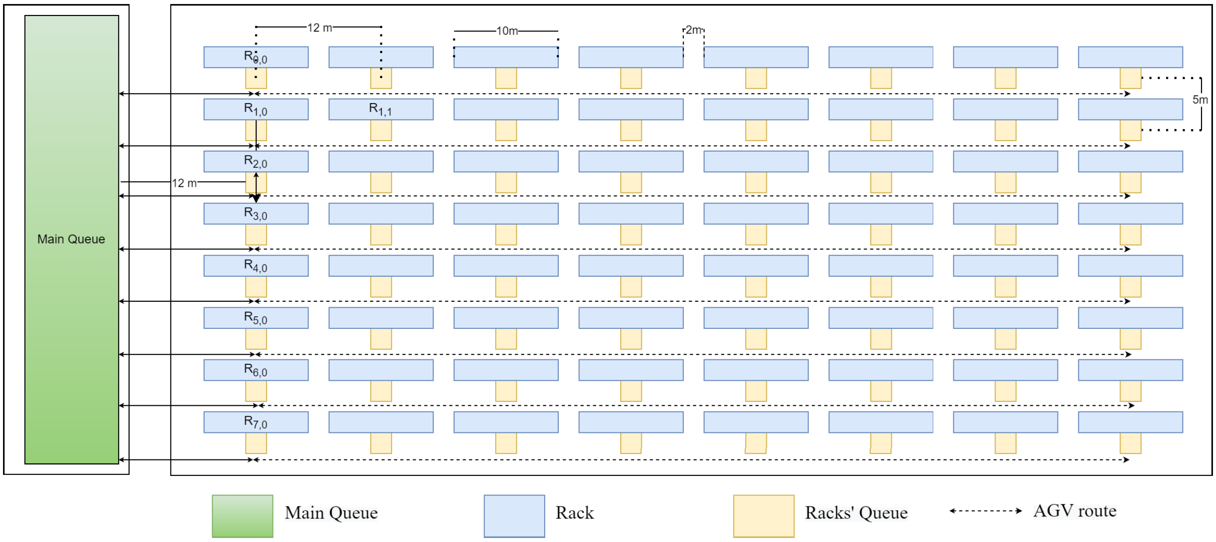


FIGURE 5. Fulfillment center storage plan for goods storing process.

or AGVs deliver the received items to the queue zones from the main queue.

Afterward, delivered items are stacked on the racks by forklift operators from each queue zone to their associated racks. As discussed above, beginner, intermediate, or professional-level transporters can follow any path based on their personal experience to deliver the items to each rack's queue zones by traveling in the storage area. Whereas AGVs follow the predetermined optimal collision-free routes to perform point-to-point delivery. The storage area consists of 8×8 racks ($R_{0,0}$ to $R_{7,7}$), and each rack has its queue zone. The length and width of each rack are 10 and 2 meters, respectively. The distance between horizontal and vertical racks is 2 and 3 meters, respectively. Racks and their associated queue zones allow for keeping received items up to 100 boxes.

B. VARIOUS SCENARIOS

Various scenarios are designed to test the efficiency of the proposed MUM-T approach compared with the baseline scheme. For the baseline scheme, human operators control the overall inbound transportation and forklift processes. Whereas in the MUM-T approach, an unmanned AGV is coupled with a manned forklift operator to perform those processes as a team.

A scenario is defined as a prearranged set of assigned racks and box frequency distributions. Here, assigned racks refer to all the non-empty racks the inbound delivered goods are eventually stored on during one batch unloading period. In each scenario, both the point-to-point item delivery phase and the item loading phase of the goods-storing process are involved. Each phase can also be divided into the overall working time achieved by the three skill levels and the MUM-T-based solution for comparison.

TABLE 3. The number of boxes and assigned racks for the five scenarios.

Scenario	Assigned Racks	Number of boxes	Box rate(λ)
1	10	232	23.2
2	20	431	21.55
3	30	558	18.6
4	40	664	16.6
5	64	1208	18.8

Table 3 represents the number of boxes, assigned racks, and average box rate for each assigned racks for each scenario. Each of the five scenarios only varies by the number and location of queues and boxes. For instance, in Scenario 1, 232 boxes must be distributed among 10 racks with an average λ =23.2 rate. In the remaining scenarios: 20, 30, 40, and 64 racks have been assigned to distribute 431, 558, 664, and 1208 boxes, respectively.

The Poisson probability distribution [33] is used to calculate the probability of the given number of boxes distribution among assigned racks (Eq. 7).

$$P(X = k) = \frac{e^{-\lambda}\lambda^{k}}{k!} \tag{7}$$

where $P(X = k)$ is the probability of k boxes being stored, λ is the average rate of box storage per rack, e is the mathematical constant approximately equal to 2.71828, and $k!$ is the factorial of k.

VI. EXPERIMENTAL RESULTS

This section of the paper presents comparative analyses of the baseline and proposed MUM-T approach results by analyzing traveling distance, time, and operational cost.

A. AGV-BASED POINT-TO-POINT DELIVERY RESULTS

The results for the inbound delivery of items from the main queue to the rack queue by different working-level

TABLE 4. Assigned parameters in the transportation process.

Transporter	Velocity (m/s)	Weight (α)	Salary($/h)
Beginner	0.6-0.8	0.2-0.3	12
Intermediate	0.8-1.0	0.1-0.2	15
Professional	1.0-1.2	0-0.1	18
AGV	0.7-0.9 m/s	0	5

operators and AGV are described in this subsection. The human operator delivers items using a transporter vehicle by choosing the paths based on their personal experience. While AGV follows the predetermined optimal path to deliver the received items from the main queue to each rack queue. Based on the five different scenarios, the traveling distance, time, and operational cost required for the delivery of items by transporter and AGV are computed using the velocity, inefficiency weights and operational salary parameters as described in Table 4.

Several factors, such as limited space, tight turns, and obstacles, can influence the velocity of human operators. Beginner and intermediate transporters have average 0.7 and 0.9 meters per second velocity. The professional operators and AGV have an average of 1.1 and 0.8 meters per second velocity. Weight (α) shows the inefficiency rate of human operators, meaning that beginner, intermediate, and professional operators have a 20%-30%, 10%-20%, and 0%-10% chance to choose a sub-optimal path, respectively. AGVs, on the other hand, have nearly 0% inefficiency weight because their optimal path has been predetermined.

Based on overall experience and efficiency rate, human operators require various operational costs (hourly salary), while AGVs require purchase, installment, and maintenance costs. One way is the cost of the AGV can be spread out over its lifespan and factored into the overall operational cost of the system [34], [35]. This cost should include the initial installation and maintenance fees, as well as any ongoing repair or replacement costs.

According to the navigation type, AGVs' cost can be between $15k (USD) and $100k [36]. In a standard project, the installation cost of magnetic, natural, and laser navigation AGVs could cost around $20k, $10k, and $40k for 3 to 4 AGVs, respectively. Other AGV peripherals, such as navigation tape and charging stations, can cost between $400 and $2k.

In this work, we considered the Wellwit 500kg capacity Lidar SLAM rotating AGV robot family [37]. The robot cost is around $27k and the manufacturer provides a one-year warranty and service. The battery life is eight hours with <1.5 hours of charging time. That robot can work about 20 hours a day. The installation cost and charging stations can be a maximum of $8k for one AGV. Therefore, one AGV's installation and purchase cost about $35k for the fulfillment center. If AGV is used around 320-340 days per year with a 20-hour work schedule, then per hour the AGV operational cost can be $5.

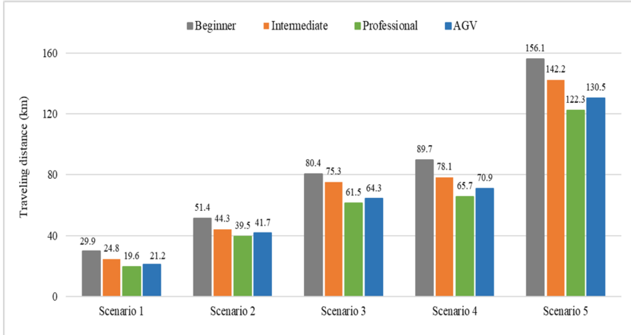


FIGURE 6. Comparative analyses of traveling distance in inbound transportation for human transporters and AGV.

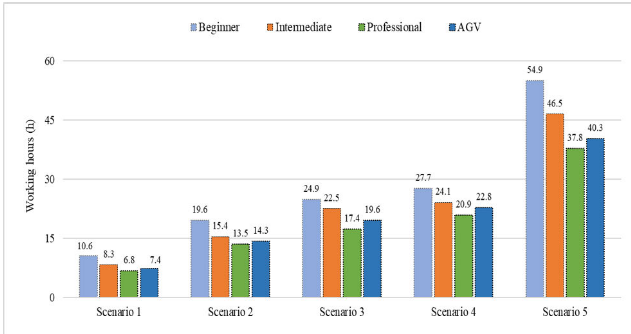


FIGURE 7. Comparative analyses of traveling time comparison results in inbound transportation for human transporters and AGV.

Fig. 6 represents comparative analyses of traveling distances for beginner, intermediate, professional, and AGV in inbound delivery. X-axes present five scenarios, while y-axes illustrate the traveling distance of vehicles. In Scenario 1, beginner, intermediate, and professional-level operators traveled 29.9, 24.8, and 19.6 km, respectively, to distribute 232 boxes among 10 assigned racks. To complete the same task, the AGV traveled 0.6 km longer compared to the professional-level operator. The former indeed follows the optimal predetermined path, but the latter has better knowledge of shortcut selections. In all scenarios, the beginner passes the longest distance compared to the remaining actors.

Overall, AGV-based point-to-point delivery has a 10% and 19.4% higher efficiency than the beginner and intermediate-level operators, respectively. However, due to a high level of experience, alternative route selection approaches professional operators to have around 6% efficiency than AGVs.

Fig. 7 represents working hours for three different working level transporters and AGV to complete the five assigned scenarios. The beginner spent 10.6, 19.6, 24.9, and 54.9 hours for five scenarios. Due to higher velocity, efficiency rate, and hourly performance, the intermediate driver could complete the assigned tasks in 8.3, 15.4, 22.5, 24.1, and 46.5 hours, respectively. The professional-level operator's and the AGV's working hours are quite similar; the latter spent about 7% more time completing all the scenarios.

TABLE 5. Assigned parameters in the forklift process.

Skill level	Speed V_f (m/s)	Ratio(β)	Load t(s)	Salary($/h)
Beginner	0.8	0.3	35	14
Intermediate	1.0	0.7	45	17
Professional	1.2	0.95	55	20
Optimal	0.8-1.2	1.0	35-55	NaN

B. TRAVELING FORKLIFT PROBLEM RESULTS

The TFP explicitly computes the optimal path ($\beta = 1.0$) and visiting nodes. This optimal path can be provided by managers, or navigation maps to the forklift operators on their personal smartphone or an embedded navigation device within the forklift. Using the optimal path selection map, all skill levels share the same travel path and this allows them to increase their efficiency. However, even if all forklift operators share the same travel path, results still vary between the skill levels due to the differences in other skill-related parameters, such as forklift driving speed and loading time per box.

The method of obtaining the results is explained as follows: For each skill level of each scenario, Algorithm 2 is run 50 times on specified *Nodes* (provided from the scenario) and β value (from Table 5) and the resulting travel distances are then averaged to obtain a single total travel distance D_f. Given the remaining parameters in Table 5, the total travel time T_d, loading time T_l, and the overall working time T for each skill level and scenario can then be calculated using Equations 3 to 5. The parameters are obtained based on an averaged collection of company data showing the operators' performances. Finally, this entire method is repeated to obtain results for the proposed approach, where the only difference in its inputs relative to the baseline configuration is that all skill levels have $\beta = 1.0$.

Table 6 represents the comparative analysis of baseline and proposed MUM-T-based optimal path selection algorithm results for items forklift process. First, according to the forklift operators' skill level, the traveling distance and time are varied in the baseline scheme. For instance, in Scenario 1, beginner and intermediate operators frequently chose the sub-optimal paths. Therefore, their traveling distances were 393 and 302 meters, respectively. A professional, on the other hand, traveled 246 meters to distribute boxes among assigned racks. Secondly, all forklift operators followed the provided MUM-T-based optimal path, therefore the traveling distance of beginner and intermediate operators has decreased remarkably. In Scenario 5, the traveling distance of the beginner operators has been decreased to 376 meters from 2158 meters (nearly 5.7 times).

The same considerations apply to traveling time optimization results. Due to inefficient traveling distances, in Scenario 3, with a baseline scheme, beginner and intermediate operators spent 22.17 and 11.55 minutes, respectively. The proposed approach allowed the traveling time to decrease to 7.23 and 5.78 minutes. Due to the different velocities of

TABLE 6. Comparative analysis of the baseline and proposed MUM-T results in forklift process.

		Distance (met)		Time (min)	
Scenario	Forklift	Baseline	MUM-T	Baseline	MUM-T
1	Begin	393	241	8.18	5.02
	Inter	302	241	5.03	4.02
	Profes	246	241	4.1	3.35
2	Begin	724	267	15.08	5.56
	Inter	460	267	7.67	4.45
	Profes	303	267	4.22	3.71
3	Begin	1064	347	22.17	7.23
	Inter	693	347	11.55	5.78
	Profes	403	347	5.6	4.82
4	Begin	1355	361	28.23	7.52
	Inter	817	361	13.62	6.02
	Profes	473	361	6.57	5.01
5	Begin	2158	376	44.95	7.83
	Intere	1190	376	19.83	6.27
	Profes	562	376	7.8	5.22

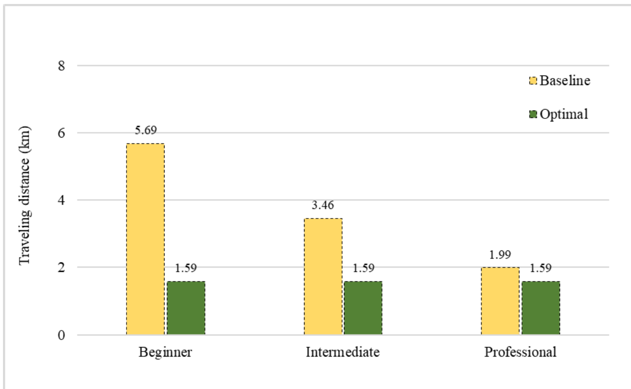


FIGURE 8. Forklift traveling distance comparison results based on baseline and proposed optimal path algorithms for all scenarios.

forklift operators, the final task completion time varied in all scenarios even though all skill-level operators traveled the same distance.

Fig. 8 compares the baseline and proposed MUM-T-based optimal path scheme results for traveling distance across all scenarios. The overall traveling distances of beginner, intermediate, and professional level operators are 5.69, 3.46, and 1.99 km, respectively. Whereas, the proposed path optimization algorithm decreases the traveling distance of operators to 1.59 km to complete forklift tasks in all scenarios. The optimal path calculation algorithm allowed the efficiency of traveling distance of beginner, intermediate and professional operators to 72%, 54.1%, and 21%, respectively.

After analyzing the overall baseline and optimal traveling distance results, we computed the overall traveling time of forklift operators. As can be seen from Fig. 9, traveling times of forklift operators are 118.6, 57.7, and 28.3 minutes, respectively. However, using the optimal path computation

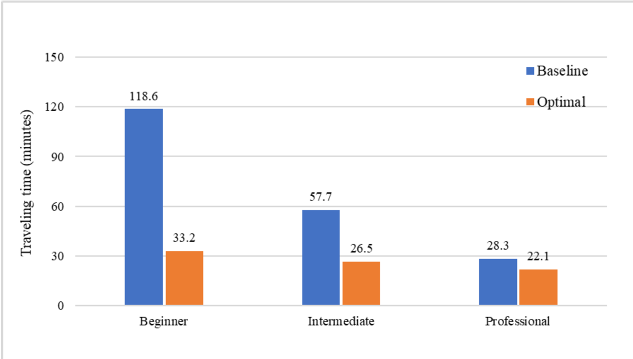


FIGURE 9. Forklift traveling time comparison results based on baseline and proposed optimal path algorithms for all scenarios.

algorithm, the traveling time of operators has decreased remarkable and required 33.2, 26.5, and 22.1 minutes of traveling time, respectively. In overall, by following the optimal path, beginner, intermediate, and professional-level operators' traveling time decreased to 71.2%, 54%, and 22%, respectively.

C. COMPARATIVE ANALYSIS OF OVERALL PROCESSING TIME AND OPERATIONAL COST

Fig. 10 presents the overall working hours for each operator and AGV. T and F represent the Transporter and Forklift operators, respectively. The point-to-point delivery time varied according to the skill level of each transporter, and the professional-level forklift operator spent the least time completing the delivery task. However, the AGV-based transportation approach has achieved fewer working hours compared to the beginner and intermediate levels of transporters.

The overall working hours of forklift operators are computed using Eq. 3, which is the result of combining the travel and loading time. Since the load time of each skill level varies, further differences in the operating time can be observed within the same scenario. For instance, forklift beginner, intermediate, and professional operators' operating times are 3.6, 3, and 2.3 hours, respectively. It can be observed that the item loading time from the rack's queue to the rack is a challenging task in the forklift process, therefore it contributes to the majority of the total operating time.

According to the overall working hours and operational expenses (Table 4 and 5) for operators, we comparatively analyzed the operational cost of the proposed approach according to the human to human, and machine-to-human teaming for all scenarios as represented in Table 7. Beginner transporter and professional forklift operators' teaming achieved the lowest operational cost in the last three scenarios in terms of human-to-human teaming, while to achieve the lowest operational costs, the professional forklift operator must be teamed with beginner and intermediate operators in the first and second scenarios, respectively.

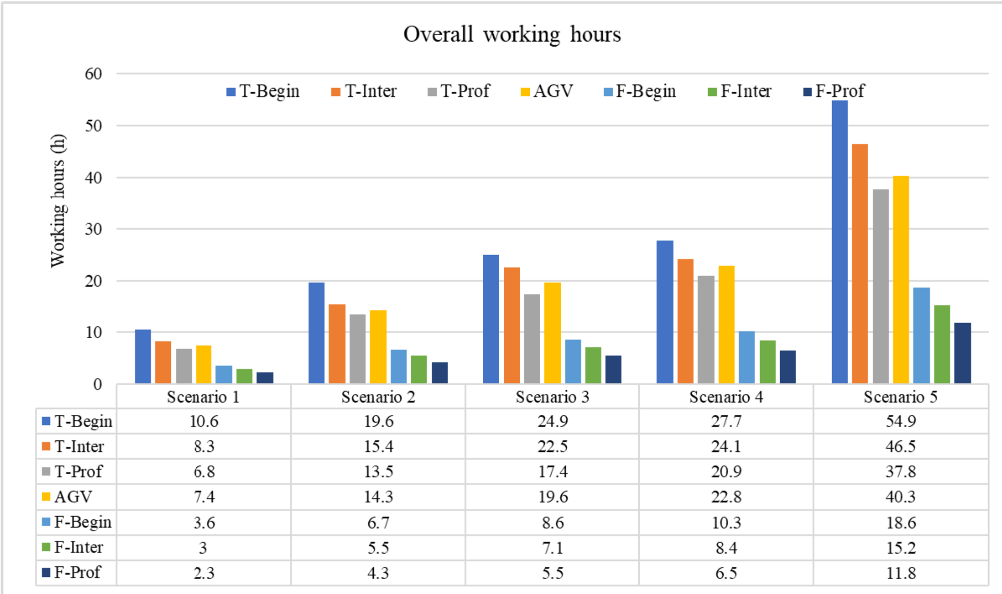
TABLE 7. Comparative analysis of operational cost in USD($).

Scenarios	Tran/Fork	Beginner	Intermediate	Professional
Scenario 1	Begin	177.6	178.2	173.2
	Inter	174.9	175.5	170.5
	Profes	172.8	173.4	**168.4**
	AGV	87.4	88	**83**
Scenario 2	Begin	329	328.7	321.2
	Inter	324.8	324.5	**317**
	Profes	336.8	336.5	329
	AGV	165.3	164	**157.5**
Scenario 3	Begin	419.2	419.5	**408.8**
	Inter	457.9	458.2	447.5
	Profes	433.6	433.9	423.2
	AGV	218.4	218.7	**208**
Scenario 4	Begin	476.6	475.2	**462.4**
	Inter	505.7	504.3	491.5
	Profes	520.4	519	506.2
	AGV	258.2	256.8	**244**
Scenario 5	Begin	919.2	917.2	**894.8**
	Inter	957.9	955.9	933.5
	Profes	940.8	938.8	916.4
	AGV	461.9	459.9	**455**

Machine-to-human teaming, on the other hand, is less expensive compared to human-to-human operational cost such as, for all five scenarios, the human-to-human teaming requires $168.4, $317, $408.8, $462.4 and $894.8 operational cost. While the AGV-to-professional forklift operator team needed $83, $157.5, $208, $244, and $455 expenses, respectively. In overall, proposed MUM-T based fulfillment center has 51% cost efficiency compared to the traditional fulfillment center.

AGVs can indeed work during the full day and night shift to perform point-to-point transportation. Human forklift operators, on the other hand, can be hired for the day shift to stack the delivered items to the racks. But the number of orders can increase remarkably in fulfillment centers during peak shopping seasons such as holidays (e.g. Christmas, Thanksgiving, Black Friday, Cyber Monday), and major sales events (e.g. Amazon Prime Day). Therefore, based on the overall working hours, we need to compute the required number of human forklift operators and AGVs for the fulfillment center by considering the parallel working as presented in Fig. 11.

Bar charts represent the number of different level forklift operators with their working hours, while line charts depict the number of AGVs with their working hours. The working hours of AGVs are remarkably high compared to forklift operators. Since the AGV robot can achieve nearly equal performance over time, increasing the number of AGVs can decrease their working hours. For instance, if we consider a single AGV and a single various forklift operator as a team, the AGV needs 7.4 hours to complete the delivery task, and 3.6, 3 or 2.3 hours are required for beginner, intermediate, and professional forklift operators to complete the task in Scenario 1. We need at least two AGVs to decrease



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
T-Begin	10.6	19.6	24.9	27.7	54.9
T-Inter	8.3	15.4	22.5	24.1	46.5
T-Prof	6.8	13.5	17.4	20.9	37.8
AGV	7.4	14.3	19.6	22.8	40.3
F-Begin	3.6	6.7	8.6	10.3	18.6
F-Inter	3	5.5	7.1	8.4	15.2
F-Prof	2.3	4.3	5.5	6.5	11.8

FIGURE 10. **Overall working hours by considering loading/unloading time of boxes.**

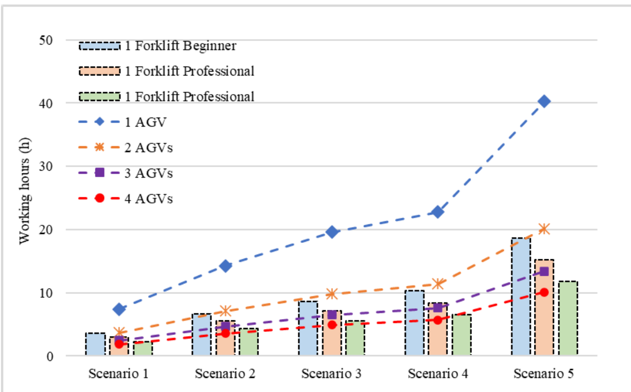


FIGURE 11. **Required number of AGV and transporters for the inbound transportation of goods.**

the overall operational time. However, as more boxes and distribution racks increase, more AGVs are required. The optimal working hours of AGVs must lie in the same line as forklift operators' working hours. Therefore, three or four AGV's can be optimal, to complete the work in the shortest time if they work on the same work shift.

VII. CONCLUSION AND FUTURE WORKS

This study offers a compelling argument for the integration of unmanned AGVs with human forklift operators in traditional fulfillment centers, proposing a MUM-T approach. This method streamlines tasks, assigning menial tasks to machines and complex, strategic ones to humans. Utilizing an AGV-based point-to-point delivery and a traveling forklift problem solution, the study illustrates significant efficiencies: a $10-19.4\%$ reduction in traveling distance for transportation and a $22-70\%$ reduction for forklift processes depending on operator experience level. Overall, this leads to a remarkable 51% operational cost efficiency improvement in e-commerce fulfillment centers, demonstrating the substantial potential of the MUM-T approach for modern logistics.

REFERENCES

[1] N. Boysen, R. de Koster, and F. Weidinger, "Warehousing in the e-commerce era: A survey," *Eur. J. Oper. Res.*, vol. 277, no. 2, pp. 396–411, Sep. 2019.

[2] L. Custodio and R. Machado, "Flexible automated warehouse: A literature review and an innovative framework," *Int. J. Adv. Manuf. Technol.*, vol. 106, nos. 1–2, pp. 533–558, Jan. 2020.

[3] T. H. D. Ho, J. Daniel, S. P. Nadeem, J. A. Garza-Reyes, and V. Kumar, "Improving the reliability of warehouse operations in the 3PL industry: An Australian 3PL case study," in *Proc. Int. Conf. Prod. Oper. Manage. Soc. (POMS)*, Dec. 2018, pp. 1–7.

[4] J. H. Kembro, A. Norrman, and E. Eriksson, "Adapting warehouse operations and design to omni-channel logistics: A literature review and research agenda," *Int. J. Phys. Distrib. Logistics Manage.*, vol. 48, no. 9, pp. 890–912, Aug. 2018.

[5] S. A. H. Shekarabi, A. Gharaei, and M. Karimi, "Modelling and optimal lot-sizing of integrated multi-level multi-wholesaler supply chains under the shortage and limited warehouse space: Generalised outer approximation," *Int. J. Syst. Sci., Oper. Logistics*, vol. 6, no. 3, pp. 237–257, Jul. 2019.

[6] G. Fragapane, R. de Koster, F. Sgarbossa, and J. O. Strandhagen, "Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda," *Eur. J. Oper. Res.*, vol. 294, no. 2, pp. 405–426, Oct. 2021.

[7] K. Azadeh, R. De Koster, and D. Roy, "Robotized and automated warehouse systems: Review and recent developments," *Transp. Sci.*, vol. 53, no. 4, pp. 917–945, Jul. 2019.

[8] R. Inam, K. Raizer, A. Hata, R. Souza, E. Forsman, E. Cao, and S. Wang, "Risk assessment for human-robot collaboration in an automated warehouse scenario," in *Proc. IEEE 23rd Int. Conf. Emerg. Technol. Factory Autom. (ETFA)*, vol. 1, Sep. 2018, pp. 743–751.

[9] N. Correia, L. Teixeira, and A. L. Ramos, "Implementing an AGV system to transport finished goods to the warehouse," *Adv. Sci., Technol. Eng. Syst. J.*, vol. 5, no. 2, pp. 241–247, 2020.

[10] A. Dhaliwal, "The rise of automation and robotics in warehouse management," in *Transforming Management Using Artificial Intelligence Techniques*. Boca Raton, FL, USA: CRC Press, 2020, pp. 63–72.
[11] D. Perkumienė, K. Ratautaitė, and R. Pranskūnienė, "Innovative solutions and challenges for the improvement of storage processes," *Sustainability*, vol. 14, no. 17, Aug. 2022, Art. no. 10616.
[12] Y. Yuan, L. Zhen, J. Wu, and X. Wang, "Quantum behaved particle swarm optimization of inbound process in an automated warehouse," *J. Oper. Res. Soc.*, vol. 74, no. 10, pp. 2199–2214, Oct. 2022.
[13] D. Zhang, L. G. Pee, and L. Cui, "Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's smart warehouse," *Int. J. Inf. Manage.*, vol. 57, Apr. 2021, Art. no. 102304.
[14] Y. Yu, X. Wang, R. Y. Zhong, and G. Q. Huang, "E-commerce logistics in supply chain management: Practice perspective," *Proc. CIRP*, vol. 52, pp. 179–185, Jan. 2016.
[15] Q. Zeng, J. He, E. Hu, and R. Wu, "Study on goods location optimization of automated warehouses in pharmaceutical companies," in *Proc. Chin. Autom. Congr. (CAC)*, Nov. 2018, pp. 3472–3476.
[16] E. Žunic, A. Beširevic, S. Delalic, K. Hodžic, and H. Hasic, "A generic approach for order picking optimization process in different warehouse layouts," in *Proc. 41st Int. Conv. Inf. Commun. Technol., Electron. Microelectron. (MIPRO)*, May 2018, pp. 1000–1005.
[17] Z. Ma, G. Wu, B. Ji, L. Wang, Q. Luo, and X. Chen, "A novel scattered storage policy considering commodity classification and correlation in robotic mobile fulfillment systems," *IEEE Trans. Autom. Sci. Eng.*, vol. 20, no. 2, pp. 1020–1033, Apr. 2023.
[18] Z. Cao, L. Zhou, C. Lin, and M. Zhou, "Solving an order batching, picker assignment, batch sequencing and picker routing problem via information integration," *J. Ind. Inf. Integr.*, vol. 31, Feb. 2023, Art. no. 100414.
[19] X. Shi, F. Deng, Y. Fan, L. Ma, Y. Wang, and J. Chen, "A two-stage hybrid heuristic algorithm for simultaneous order and rack assignment problems," *IEEE Trans. Autom. Sci. Eng.*, vol. 19, no. 4, pp. 2955–2967, Oct. 2022.
[20] C. Bunterngchit and S. Leepaitoon, "Simulation-based approach for reducing goods loading time," in *Proc. 8th Int. Conf. Modeling Simulation Appl. Optim. (ICMSAO)*, Apr. 2019, pp. 1–5.
[21] J. Li, R. Wang, and S. Wen, "Research on path optimization of automated warehouse based on heuristic ant colony algorithm," in *Proc. 33rd Chin. Control Decis. Conf. (CCDC)*, May 2021, pp. 7409–7413.
[22] F. J. Perez-Grau, J. R. Martinez-de Dios, J. L. Paneque, J. J. Acevedo, A. Torres-González, A. Viguria, J. R. Astorga, and A. Ollero, "Introducing autonomous aerial robots in industrial manufacturing," *J. Manuf. Syst.*, vol. 60, pp. 312–324, Jul. 2021.
[23] C. K. Lee, "Development of an industrial Internet of Things (IIoT) based smart robotic warehouse management system," in *Proc. Int. Conf. Inf. Resour. Manage. (CONF-IRM)*, 2018, p. 43.
[24] M. Aqeel, F. Ali, M. W. Iqbal, T. A. Rana, M. Arif, and R. Auwul, "A review of security and privacy concerns in the Internet of Things (IoT)," *J. Sensors*, vol. 2022, Sep. 2022, Art. no. 5724168.
[25] C. Higgins, L. McDonald, M. I. Ul Haq, and S. Hakak, "IoT hardware-based security: A generalized review of threats and countermeasures," in *Security and Privacy in the Internet of Things: Architectures, Techniques, and Applications*. Hoboken, NJ, USA: Wiley, Dec. 2021, pp. 261–296.
[26] H. Tang, A. Wang, F. Xue, J. Yang, and Y. Cao, "A novel hierarchical soft actor-critic algorithm for multi-logistics robots task allocation," *IEEE Access*, vol. 9, pp. 42568–42582, 2021.
[27] S. Delalic, E. Žunic, A. Alihodžic, and E. Selmanovic, "The order batching concept implemented in real smart warehouse," in *Proc. 43rd Int. Conv. Inf., Commun. Electron. Technol. (MIPRO)*, Sep. 2020, pp. 1685–1690.
[28] M. Savsar, "Optimization of location of a distribution center for an automobile supply chain system," in *Proc. 3rd Int. Congr. Hum.-Comput. Interact., Optim. Robotic Appl. (HORA)*, Jun. 2021, pp. 1–6.
[29] Y.-H. Jo and C. Choi, "A study on the architectural changes of the logistics center due to automation and enlargement-focusing on the case of coupang, e-mart, Amazon logistics centers," *J. Architectural Inst. Korea Planning Design*, vol. 36, no. 1, pp. 37–48, Jan. 2020.
[30] V. Pesqué-Cela, J. Li, and Y. K. Kim, "Overcoming the liability of foreignness in U.S. capital markets: The case of Alibaba and coupang," *Asia Pacific Bus. Rev.*, vol. 29, no. 2, pp. 323–349, Sep. 2022.
[31] D. L. Applegate, R. E. Bixby, V. Chvátal, and W. J. Cook, "The traveling salesman problem," in *The Traveling Salesman Problem*. Princeton, NJ, USA: Princeton Univ. Press, 2011.
[32] W. B. Nordgren, "Flexible simulation (flexsim) software: Flexsim simulation environment," in *Proc. 35th Conf. Winter Simulation: Driving Innov.*, 2003, pp. 197–200.
[33] J. Letkowski, "Applications of the Poisson probability distribution," in *Proc. Acad. Bus. Res. Inst. Conf*, 2012, pp. 1–11.
[34] L. S. Valamede and A. C. S. Akkari, "Lean 4.0: A new holistic approach for the integration of lean manufacturing tools and digital technologies," *Int. J. Math., Eng. Manage. Sci.*, vol. 5, no. 5, pp. 851–868, Oct. 2020.
[35] V. K. Chawla, A. K. Chanda, and S. Angra, "The scheduling of automatic guided vehicles for the workload balancing and travel time minimi-zation in the flexible manufacturing system by the nature-inspired algorithm," *J. Project Manage.*, vol. 4, no. 1, pp. 19–30, May 2019.
[36] A. Pastor. (2023). *Your Vehicle-Our Tech*. Accessed: Mar. 5, 2023. [Online]. Available: https://tinyurl.com/nhyvauvc
[37] H. Peng. (2023). *Made-in-China*. Accessed: Mar. 5, 2023. [Online]. Available: https://tinyurl.com/54zch6j7

AZIMBEK KHUDOYBERDIEV received the B.S. degree from the Tashkent University of Information Technologies, Uzbekistan, in 2018, and the M.S. degree from the Department of Computer Engineering, Jeju National University, South Korea, in 2020. He is currently pursuing the Ph.D. degree with the Department of Computer Science, The State University of New York, Korea (SUNY Korea). His research interests include the development of the Internet of Things, computer vision, and deep learning-based autonomous systems.

SHUBHANGI S. R. GARNAIK received the B.Tech. degree from the Cummins College of Engineering, Pune, India, in 2019. She is currently pursuing the M.S. degree with the Department of Computer Science, The State University of New York, Korea (SUNY Korea). Her research interests include deep learning, computer vision-based smart systems, and multimedia applications in AR and natural language processing.

HA YOUNG KIM received the B.S. degree in mechanical engineering from The State University of New York, Korea (SUNY Korea), in 2019, where he is currently pursuing the M.S. degree with the Department of Computer Science. His research interests include analyzing and improving embedding in recurrent neural networks and transformers for natural language processing.

JIHOON RYOO received the B.S. and M.S. degrees in electrical engineering from the Korea University, Seoul, South Korea, in 2007 and 2010, respectively, and the Ph.D. degree in computer science from Stony Brook University, Stony Brook, NY, USA, in 2017. In 2017, he joined the Department of Computer Science, The State University of New York, Korea (SUNY Korea), Incheon, South Korea, where he is currently an Assistant Professor. His current research interests include mobile/wireless networking, battery-less communication, multimedia in VR, and gaze-assisted networking systems and their evaluation.