MATEC Web of Conferences **388**, 04021 (2023) https://doi.org/10.1051/matecconf/202338804021
2023 RAPDASA-RobMech-PRASA-AMI Conference

Optimised path planning of a UAV for inventory management applications

Thabisa Maweni[1*], *T*iro Setati[1], and *Natasha* Botha[1]

[1]Centre for Robotics and Future Production, Manufacturing Cluster, Council for Scientific and Industrial Research, South Africa

Abstract. Inventory management in warehouses is a crucial task in the logistics industry. Manual stocktaking in larger-scale warehouses can be time-consuming and labour-intensive. To automate this process, unmanned aerial vehicles (UAVs) have gained popularity due to their potential to offer a safer, timeous, and more efficient solution. However, deploying drone systems can face challenges and therefore requires planning tasks such as path planning. This study investigates two commonly used UAV flight paths to identify the optimal path within a warehouse: zigzag and up-down flight paths. A Gazebo simulation was considered with a six-rotor UAV model to analyse the different flight paths. The accuracy of both path types is measured for comparison, and flight times were considered as a means for optimisation. The results indicated that the zigzag flight path is the most optimal with the shortest flight time. The study found that the zigzag path resulted in a 27.25% shorter estimated flight time compared to the up-down path.

1 Introduction

There has been a rise in the utilisation of unmanned aerial vehicles (UAVs), otherwise known as drones, over the last few years [1 - 3]. The rise of UAVs can be attributed to their potential to enhance the efficiency of tasks typically performed by humans, thanks to their autonomous mobility. Moreover, they have proven to be cost-effective and safer alternatives for human workers. UAVs can navigate and access areas that are usually deemed unsafe and hazardous for humans, mitigating risks and reducing operational expenses [4]. While drones have been shown to have applications across various industries, one of the use cases of interest is logistics. Some innovative drone applications in the logistics industry include package delivery applications within smart factories and inventory management. The growth in industrialisation and e-commerce, which led to the increase in the scale of warehouses [2], has intensified the need to increase efficiency in inventory management processes. Inventory management in warehouses is a vital function for the traceability of products, and as such, there has been an uptake of drone technology to assist in making the process more efficient [1]. Twelve use cases of UAV applications in indoor warehouse environments were identified by Wawrla et al. [2]. These applications range from indoor intra-logistics

* Corresponding author: tmaweni@csir.co.za

applications, inspection, and surveillance to inventory management. Inventory management has shown the most potential and growth in warehouse operations. UAVs in this area promise to increase accuracy, reduce labour costs, and minimise dangerous tasks for staff [5].

Stock-taking is usually done by manually scanning each item's barcode in the warehouse and counting the units to verify the stock. Performing the task manually can become time-consuming and labour-intensive, especially considering larger warehouses. Therefore, UAV-assisted stocktaking proposes a safer, timeous, and optimised solution [2,4]. UAVs are preferable in some cases as they can reach potentially dangerous areas in the warehouse that the staff couldn't reach safely or without specialised equipment. However, the practical deployment of these vehicles in warehouses is complex and can present some challenges. Using smaller UAVs in tightly structured indoor spaces is favourable due to their manoeuvrability (especially compared to ground-based vehicles). However, flying smaller UAVs presents even more challenges as their operation can be limited by their shorter battery life [1, 5]. For these reasons, deploying UAVs in such environments requires proper planning.

This paper investigates the planning of UAV flight paths with a focus on optimising the flight time during its inventory-taking operations in a warehouse setting. A UAV model will explore different flight paths in a simulated environment. Flight elements contributing to the optimal route will be identified through experimentation. These experiments include monitoring the position of the UAV with respect to the shelves during operation, the horizontal and vertical movements of the drone, and time delays between each movement, allowing product identification between each shelving unit. The goal is to work as quickly and as accurately as possible therefore the level of accuracy between the different routes will be considered.

2 Literature Review

Efficient path planning is crucial for optimising UAV-assisted inventory management processes and improving operational efficiency. This literature review aims to explore the existing research on UAV route planning and its relevance in the context of industrial warehouses for inventory management.

One notable study in the field of UAV route planning is the work by Liu et al. [6], which focuses on optimising UAV routes for road segment surveillance. Although the primary focus of this study is traffic surveillance, it offers valuable insights and methodologies that can be adapted to UAV route planning in industrial warehouses. In their research, Liu et al. propose a multi-objective optimisation model for planning UAV routes to minimise cruise distance and the number of UAVs used. They introduce an evolutionary algorithm based on the Pareto optimality technique to solve the multi-objective UAV route planning problem. Their UAV flight experiment results demonstrate a significant decrease in optimised cruise distance and the number of UAVs used. The multi-objective optimisation model can be adapted to consider factors specific to warehouse environments, such as warehouse structure and inventory layout. By minimising travel distance and the number of UAVs used, warehouse managers can ensure timely and accurate inventory management, leading to improved productivity and cost savings. Furthermore, the study by Liu et al. highlights the impact of road segment lengths on UAV route planning. This finding can be translated to warehouse environments, where the size and layout of storage areas can vary. By analysing the impact of different warehouse configurations on UAV route planning, warehouse managers can optimise the layout and organisation of inventory to facilitate efficient UAV operations.

Cristiani et al. [1] acknowledge that warehouse management is a crucial task for businesses and that the usage of UAVs has been proposed to automate the inventory process while increasing safety for human workers. The paper by Cristiani et al. presents a comprehensive study on UAV-based inventory management in large-scale warehouses. The authors address the challenges of indoor navigation, package identification, and limited flight autonomy faced by UAV swarms in warehouse environments. They propose a generic architecture that includes components for UAV path planning, package identification using QR codes, data validation through the Blockchain, and wireless charging. This architecture can be adapted to suit a specific warehouse environment and a specific UAV-based inventory management system. The study also analyses the trade-off between inventory accuracy and completion time, deriving optimal UAV mobility parameters in terms of speed and number of visits for each shelf unit. This analysis provides insights into optimising the mobility parameters to achieve the desired balance between accuracy and efficiency. The authors conduct a proof-of-concept implementation using low-cost mini-drones and single-board computers, providing practical insights into the system's performance. This paper serves as a valuable reference for researchers and practitioners interested in UAV route/path planning for inventory management in industrial warehouses.

The paper mentions several technical issues that need to be addressed for the practical deployment of UAV swarms in warehouse environments, such as indoor navigation, package identification, and limited flight autonomy. The work presented in this paper focuses on tackling limited flight autonomy and improving the efficiency and effectiveness of inventory management using UAVs.

3 Methodology

This section presents the approach that was followed for this work. A description of the proposed architecture, the simulation environment and the chosen UAV model are presented and described in the following subsections. Additionally, a detailed description of the experimental setup is provided.

3.1 Proposed Architecture

The proposed inventory management system considered is adapted from Cristiani et al. [1] and is depicted in Figure 1. It includes a simulated warehouse, one UAV model and a ground control station. The ground control station (GCS) is a computer which is on the same network as the UAV. In this case, by virtue of the work being in simulation, the GCS is the computer running the simulation (i.e., launching the UAV model and the flight controller).

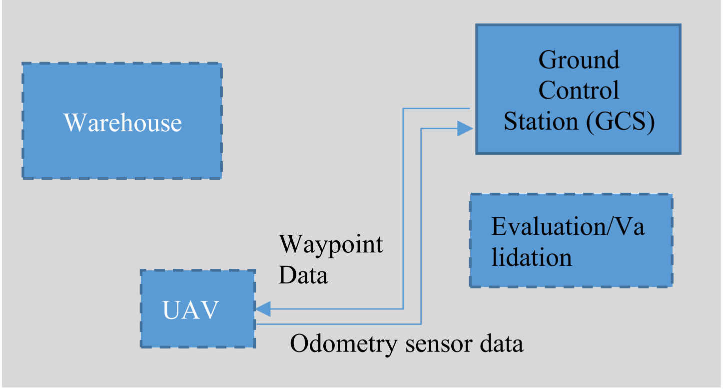


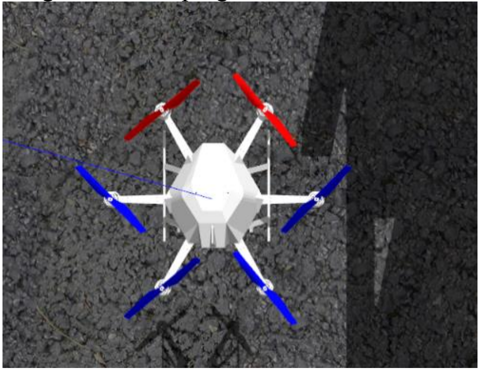
Fig. 1. Proposed drone assisted inventory taking system. The elements with dashed line borders all reside within the GCS for the simulation.

The experiments performed can be split into three parts:

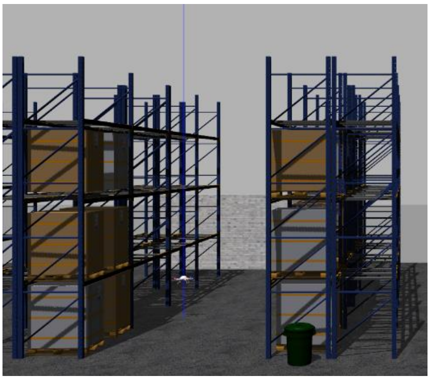
- Mobility,
- Flight time, and
- Flight trajectory evaluation.

3.2 Simulation Environment

To reduce the chance of collisions, and either reduce the time required to train a new pilot or the cost associated with using a trained pilot, it was decided to perform the study in a simulated environment. RotorS, a ready to use Gazebo Micro Aerial Vehicle (MAV) simulator, was used to perform the simulated experiments and determine the optimal flight path. Gazebo is an open-source simulation environment used to provide realistic conditions for developing robotics. RotorS was selected as the simulator because its different components (e.g., controllers, state estimators, etc.) were designed to be comparable to their real-world counterparts [8]. It is, therefore, possible to implement the same controllers and their parameters from the simulator on a real-world UAV without any modifications. The UAV model selected is an Iris quadrotor, shown in Figure 2.A simulated odometry sensor is used to provide the position, orientation, and linear and angular velocities of the drone through a Gazebo plugin.



(a) Astec Firefly six-rotor UAV model in a Gazebo world, the red blades indicate the front of the UAV.



(b) Simulated warehouse.

Fig. 2. Simulated warehouse and drone model. (a) Astec Firefly six-rotor UAV model in a Gazebo world and (b) Simulated warehouse.

The warehouse shown in Figure 2(b) consists of shelve units and aisles where each unit contains a package. It is assumed that each package is visible from the aisle and has its own unique identifier, such as a barcode or QR code in a smart warehouse. The warehouse structure assumed for the experiments is shown in Figure 3. It has 4 rows of shelves, and each shelf contains three 3 m x 3 m shelfing units. Each unique identifier is represented by a small square located at the centre of each shelf unit. The locations of the unique identifiers are used to set the position waypoints to send to the drone. For all experiments, the drone starts its trajectory 1.5 m above the ground at zero x- and y-coordinates, and the drone passes over the centre of each shelf during operation.

3.3 Experimental Setup

As mentioned previously, three experiments will be performed. First, a mobility test to ensure that the UAV could fly in a parallel motion to the shelve according to the zigzag path and to also ensure that it can move vertically according to the up-down path. This is followed by a flight time test to determine how long it takes for each flight to complete the desired path successfully. Lastly, an evaluation test to measure the accuracy of each flight path.

3.3.1 Mobility Test

To test the mobility the drone is given a set of positional waypoints to direct its flight path. This test was conducted with and without a position controller. The controller used is an attitude PID position controller implemented through the mav_controller package. To visualise the drone's odometry, Rviz was used. Rviz is a 3D visualisation tool used to visualise robot models and sensor data. The waypoints passed into the simulation consisted of a waypoint time delay (t), position (in x-, y- and z-coordinates) and a yaw angle (θ) for rotation. To assess the drone's ability to fly parallel to the shelves while moving horizontally, constant y- and z-values were maintained using the waypoints, the yaw angle was set to zero, and the x-coordinate varied. Similarly, to evaluate the vertical movement, the x- and y-coordinates were kept constant, the yaw angle was set to zero, and only the z-coordinate was varied. The simulation relied on RotorS's built-in ideal odometry sensor to monitor the UAV's position by assessing its published data.

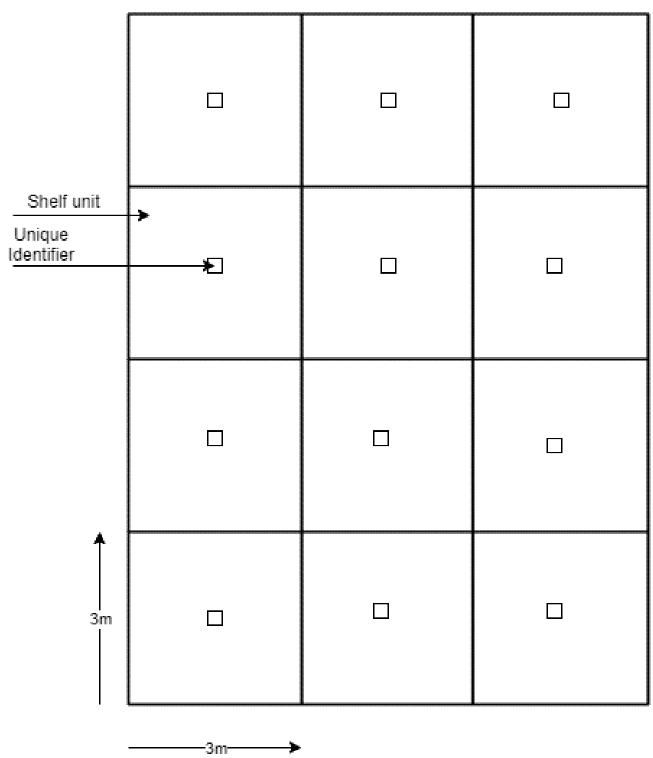


Fig. 3. Front view of a stacked shelf in the warehouse structure.

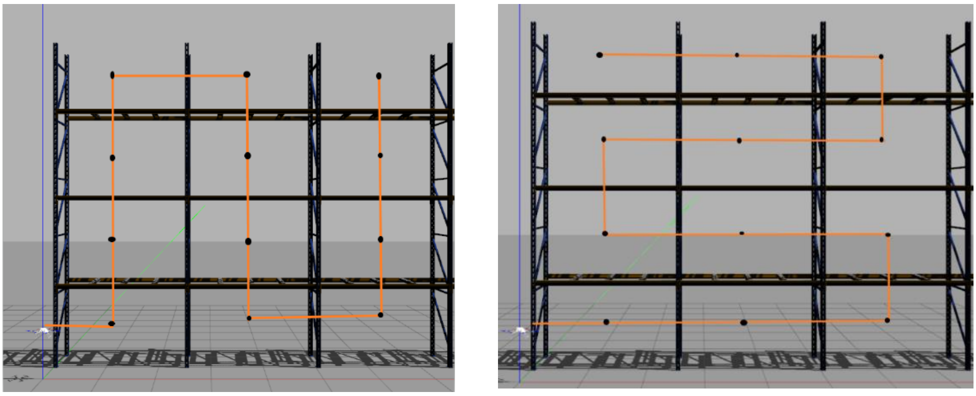
3.3.2 Flight Trajectory Evaluation

Next, waypoints were chosen according to the desired path as illustrated in Figure 4, and sent to the drone to follow:

a. The up-down, and
b. the zigzag flight paths.

The UAV flies to the centre of the first shelf unit with its front facing the shelves. A time delay is implemented at each shelf unit, or waypoint, to account for processing or capturing of the unique product identifier. It then travels to the next unit according to the waypoints planned and returns to its home position before landing. Between the paths, the time delay at a waypoint is kept constant to ensure the results of both tests are comparable. The time delays were varied between experiments to optimise the flight time while giving enough time at each waypoint so that the flight path follows a discrete movement. For each flight, the duration was recorded to compare the performance.

Three shelving scenarios were considered. The first warehouse scenario had 4 rows and 3 columns as seen in Figure 4. For the second scenario, we added a column to extend the shelfing to 4 rows and 4 columns and for the third scenario we added a row to extend the first scenario to 5 rows and 3 columns.



(a) Up-down UAV path (b) Zigzag UAV path

Fig. 4. Overview of drone path parallel to the shelves. The drone starts 1.5m above the ground in both cases, with its front facing the shelves.

3.3.3 Accuracy Measurements

Lastly, the accuracy of each proposed flight path was measured and analysed. The aim of this test was to track the UAV's location and compare it with the desired location specified to evaluate how well the UAV can follow the given waypoint and for how long can it maintain that given position. Ultimately, this error aims to measure the accuracy of the drone in positioning itself at a given waypoint.

For each path, the odometry of the UAV was recorded as it flies storing these results in a log file while running the simulation. The error at each waypoint is calculated using the root mean square error (RMSE) for both position and angular velocity tracking. The RMSE is a standard method to measure the error between data predicted by a model and the data observed. It is defined as:

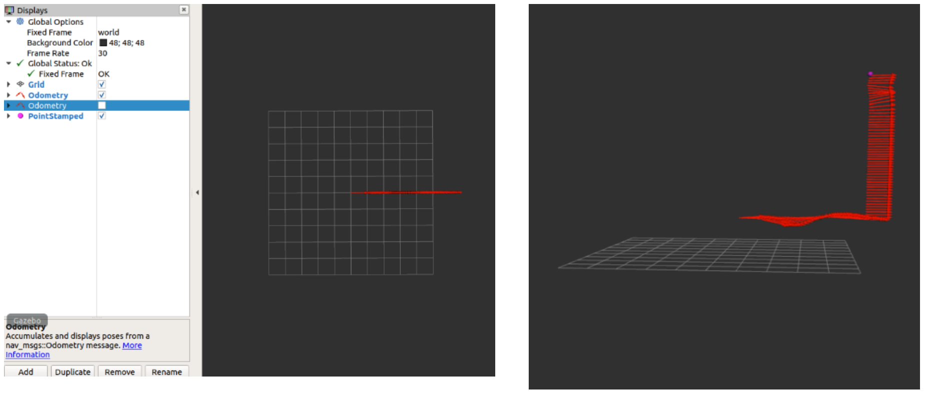
$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (1)$$

Where $\hat{y}_i$ is the predicted value, y_i is the observed value and n the number of observations.

The RMSE was determined for both vertical and horizontal flight movements. The average position error and the settling times were considered at waypoint position.

4 Results and Discussion

The results for the mobility test are shown in Figure 5. Figure 5(a) illustrates the odometry of the UAV when given position waypoints where the x-coordinate is varied and the y- and z-coordinates are kept constant. No variations are visible in the y-axis and therefore it was deduced that the UAV can fly parallel to the shelves. Similarly, the UAV can fly in a straight line with small variations in the z-axis as seen in Figure 6(b). Here the movement of the UAV, when given waypoints by varying the z-coordinates, illustrates that only the z-coordinate is changing which is the desired behaviour.



(a) The x-y plane with varied x-coordinates.

(b) The x-z plane with varied x- and z-coordinates.

Fig. 5. UAV Odometry for given waypoints showing no undesired horizontal movement when the z-coordinates are varied. The variation in the vertical movement is negligible when x-coordinates are varied.

For both flight paths, the position error was estimated for multiple waypoints as illustrated in Figure 6. Considering Figure 6, there is a noticeable position error on waypoint 0 of 0.260 m, but the evaluation was performed 5 s (40 s after the simulation started) after the first waypoint is executed. The average position error is minimal at 0.025 m as there is no noise on the sensor. This is an insignificantly small error due to the use of an ideal odometry sensor. It is worth noting that the controller considered can achieve every waypoint with minimal error. However, the settling time, the amount of time it takes for the drone to hover at the desired waypoint, was different for the zigzag and up-down flight paths.

To consider the waypoints of a vertical trajectory, upward waypoints were provided and the settling time for each waypoint was calculated. An example of the output generated for this test is shown in Figure 6. The settling time for the UAV is longer while performing horizontal movements (3.218 s) compared to the upward (2.184 s) or downward (2.292 s) movements. In an attempt to provide comparable and consistent behaviour, the time delay along the vertical path was experimented with. It was found that by increasing the time delay before executing each vertical waypoint, from 5 s to 8 s in the simulation, and keeping the time delays at 5 s for horizontal movements, provides comparable results between the two flight paths.

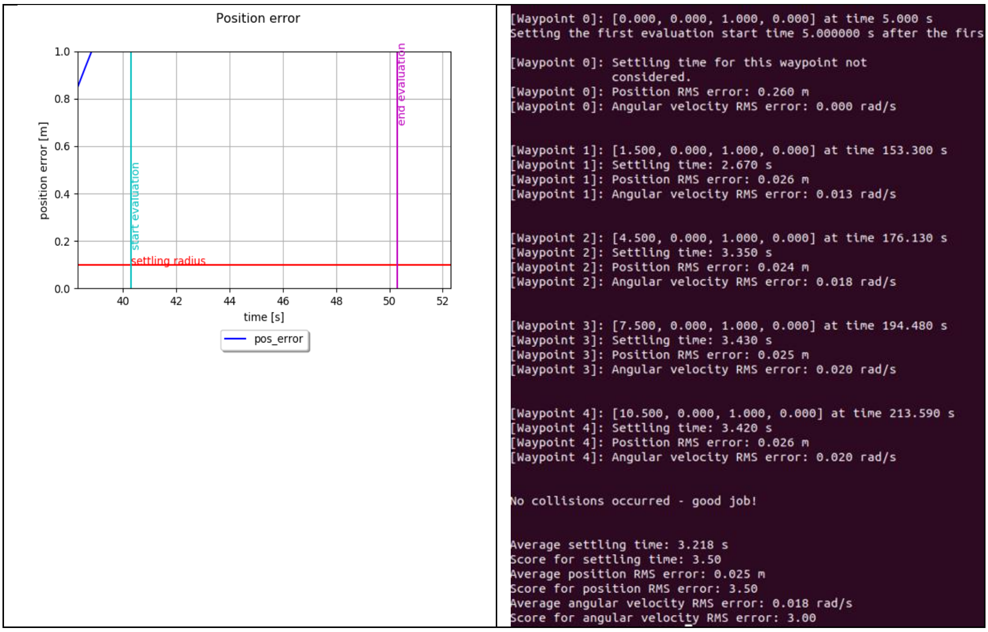


Fig. 6. Position error plot for multiple waypoints with no noise on the odometry sensor with the terminal output for a RMSE evaluation.

Table 1 presents the experimental results of the different flight paths between the different shelving scenarios with the settling times considered. The up-down path has more vertical movements and therefore takes longer to complete for the same warehouse scenario. It can be noted that for a shelving setup that is higher (scenario 3), the difference in the trajectory duration between the two paths is relatively lower than for other scenarios. It is evident from these results that the zigzag path takes the least amount of time to complete, irrelevant of the scenario.

Table 1. Flight trajectory times.

Warehouse Scenario	Experiment no.	Path	Trajectory duration	Percentage Difference of flight time.
Warehouse 1	1	Zigzag	00:56.79	38.65%
	2	Up-down	01:32.56	
Warehouse 2	3	Zigzag	01:17.16	29.48%
	4	Up-down	01:49.42	
Warehouse 3	5	Zigzag	01:40.02	13.62%
	6	Up-down	01:55.80	

The estimated time difference as a percentage between the two path types is estimated in Table 1 with the highest time difference of 38.65% in warehouse scenario 1 and the lowest difference of 13.62% in warehouse scenario 3. The average time difference is 27.25%. This means that if the UAV takes 30 minutes to complete stock taking of one aisle according to the zigzag path, it will take about 4,08 minutes more according to the up-down path. Since the difference is relatively minimal, other factors may be investigated to determine the most optimal route in addition to flight time.

5 Conclusion

This paper considered two flight paths, namely the zigzag and the up-down path to identify the optimal flight path for a UAV performing stock taking in an indoor warehouse. Gazebo simulation-based experiments were conducted to analyse the two paths and measure flight times.

The results showed that the zigzag path had a shorter flight time in comparison to the up-down path for the different warehouse scenarios considered. This suggests that the zigzag path is the more optimal when considering the overall flight time during a stock taking process. It should be noted that the results are depended on the UAV, and flight dynamics of the UAV used could therefore vary. With that in mind, the methodology followed provides a path planning approach to identifying the optimal route for UAV-assisted stocktaking.

For future work and to further investigate the efficiency of the paths, the energy consumption of the UAV when flown according to the two paths would be measured through physical experiments. Using the physical counterpart of the simulated UAV model, the experiments will be conducted to validate the results presented in this paper.

References

1. D. Cristiani, F. Bottonelli, A. Trotta, M. Di Felice*, Inventory Management through Mini-Drones: Architecture and Proof-of-Concept Implementation*, in Proceedings **-** 21st IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks, WoWMoM, Aug., (2020)
2. L. Wawrla, O. Maghazei, T. Netland, *Whitepaper-Applications of drones in warehouse operations*, 2019, Available: www.pom.ethz.ch
3. A.Gupta, T. Afrin, E. Scully, N. Yodo, *Advances of UAVs toward Future Transportation: The State-of-the-Art, Challenges, and Opportunities.* Future Transportation. 1. 326-350, Sept. (2021)
4. M. Gubán, J. Udvaros, *A Path Planning Model with a Genetic Algorithm for Stock Inventory Using a Swarm of Drones*, Drones **6**, 11, Nov., (2022)
5. W. Kwon, J.H. Park, M. Lee, J. Her, S.H. Kim, J.W. Seo, *Robust Autonomous Navigation of Unmanned Aerial Vehicles (UAVs) for Warehouses' Inventory Application.* IEEE Robotics and Automation Letters, *5*(1), 243–249 (2020)
6. X. F. Liu, Z. W. Guan, Y. Q. Song, D.S. Chen, *An optimization model of UAV route planning for road segment surveillance*. Journal of Central South University, 21(6), 2501–2510.(2014)
7. E. Companik, M. J. Gravier, M. T. Farris, *Feasibility of warehouse drone adoption and implementation*, J.Transp. Manag, **28,** 2, pp. 31–48, Jan. (2018)
8. F. Furrer, M. Burri, M. Achtelik, R. Siegwart*, RotorS—A modular gazebo MAV simulator framework*, Stud. Comput. Intel **625**, pp. 595–625, Feb. (2016)

9. DJI, DJI Air 2S, Available at: https://www.dji.com/global/air-2s/specs. Last accessed on: 19 June 2023