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Evolutionary Algorithm-Based Energy-Aware Path Planning with a Quadrotor for Warehouse Inventory Management

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Abstract

Quadrotors have been vital for automating warehouse processes. However, a significant gap in recent studies is that they use a single quadrotor with limited battery life, considering that their objective involves navigation in a large-scale environment such as a warehouse. Using an energy consumption model to enable more efficient navigation can be explored. Conventional data-driven energy models and path planning algorithms are insufficient for describing the various motions that a quadrotor can perform in warehouse operations, such as changes in yaw. This study aims to design a novel exhaustive data-driven energy consumption model and evolutionary algorithm-based path planning algorithm to consider various quadrotor movements involved in warehouse operations. The quadrotor is tasked with performing a set of movements to each be represented as a power equation in terms of their velocity. The obtained equations were subsequently used as the primary optimization objective for the path planning algorithm, which included yaw angle objectives and constraints. A set of experiments was performed with Crazyflie quadrotors to verify the model and the algorithm. The results showcased the accuracy of the energy consumption model, which was kept at a maximum difference of 0.6%. The designed path planning algorithm obtained greater energy efficiency in the generated paths compared to other state-of-the-art evolutionary algorithms with similar objectives and constraints.

Keywords: Evolutionary Algorithms; Inventory Management; Path Planning; Quadrotor; Warehouse.

1. Introduction

Warehouses serve as vital hubs in supply chains, as global consumer demand has significantly risen in recent years. These warehouses perform periodic inventory management to address the ever-increasing complexity of managing goods, as scanning technologies such as barcodes and RFID tags have been incorporated to improve productivity [1]. With most goods requiring a lift to reach, studies have examined the viability of quadrotors for warehouse applications. Quadrotors can be equipped with sensors that allow them to perform meaningful tasks. These methods have seen high usage in warehouse processes, among which, as compiled by Malang et al. [2], include stocktaking [3], cyclic counting [4], and drone-based deliveries [5].

Studies that have investigated integrating quadrotors in warehouses mostly employ scanning sensors for identification technologies such as barcodes, *Quick Response* (QR) codes, and *radio frequency identification* (RFID) tags. Alajami et al. [6] investigated the use of signals received from RFID tags attached to goods for a quadrotor to navigate a warehouse

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environment. In another study, Yang et al. [7] developed *convolutional neural networks* (CNNs) to detect QR codes from images captured by a quadrotor. Similarly, Kalinov et al. [3] used a CNN to process barcodes with a camera-equipped quadrotor. As the use of cameras with quadrotors has advanced in addition to advancements in neural networks, further research should consider quadrotor yaw angles for easily detecting tags from products. The change in quadrotor yaw also corresponds to a nonnegligible increase in energy consumption, which should be managed carefully during long-term operations performed in large-scale warehouse environments.

Energy consumption models were investigated early in the literature to estimate the energy required by a quadrotor to peruse a flight plan. Di Franco & Buttazzo [8] developed a data-driven energy consumption model to estimate the power consumption of a quadrotor during pure straight flights and pure yaw changes given its velocity. They also identified an optimal speed for straight flights to maximize energy efficiency. Yan et al. [9] estimated the energy of a quadrotor by defining a constant value of energy per length of the path traveled. Some studies have derived an energy consumption model based on calculations made from the dynamics of the quadrotor rather than performing experiments to gather data. Na et al. [10] derived the battery consumption of a quadrotor by measuring its expected output power based on factors such as voltage, current, and motor torque. On the other hand, Liu et al. [11] based their energy model on forces acting on a quadrotor during flight. Using the approach of the previous two studies would require extensive knowledge of the specific quadrotor dynamics, which may require additional testing with specialized equipment. However, data-driven approaches can sufficiently derive an energy model for a quadrotor. However, the maneuvers that previous studies considered do not reflect the wide range of motions that quadrotors can access. In warehouse operations, yaw changes are crucial alongside simultaneous straight flights and changes in elevation to fully describe the energy consumed by the quadrotor.

Apart from energy efficiency, a path planning algorithm is necessary to direct the quadrotor to the product to be scanned. Since inventory control in warehouse operations is time sensitive, the algorithm should provide near-optimal solutions quickly. Various algorithms can be found in the literature, each with advantages and drawbacks [12]. *Genetic Algorithm* (GA) and *Particle Swarm Optimization* (PSO) are two of the more widely used algorithms under *Evolutionary Algorithms* (EA). In particular, PSO uses a set of solutions encoded as particles, which update iteratively based on the best solutions found so far as to be evaluated by a fitness function. The *Comprehensively Improved PSO* (CIPSO) algorithm utilizes adaptive weights or parameters to prevent the algorithm from falling into a local optimum solution and allowing faster convergence at the late phase [13]. The *Comprehensive Learning and Dynamic Multi-Swarm PSO* (CL-DMSPO) divides particles into subswarms, accomplishing the same goal as CIPSO [14]. Na et al. [10] implemented PSO with objectives based on the weighted sum of path distance, energy consumption, and collision avoidance factor.

The time-sensitive nature of inventory management and its execution in a large-scale warehouse environment require a time-efficient energy-aware path planning algorithm. Near-optimal paths that minimize the energy consumption of a quadrotor need to be generated, given its limited battery life. Moreover, the energy model should consider the variety of movements available to the quadrotor during flight. As conventional evolutionary-based path planning algorithms mainly optimize flight distance, minimizing the energy consumed by the generated path based on the designed model would be beneficial. As evolutionary algorithms exhibit flexibility in optimization problems, the quadrotor yaw can be incorporated into the fitness function because a change in yaw speed contributes to overall energy consumption.

This study aims to address the gaps observed in quadrotor-aided inventory management by designing an evolutionary-based energy-aware path planning algorithm suitable for application given the selection of quadrotors. Specifically, the objectives of the study are as follows:

- To design a data-driven energy consumption model for a crazyflie quadrotor based on the energy recovered after it performs a maneuver,
- to design a path planning algorithm and decision control system for automated inventory management with minimization of energy consumption based on the developed model and
- to implement the algorithm through simulations to verify its feasibility with quadrotors.

This paper introduces a framework for designing a data-driven energy consumption model for a quadrotor considering other motions, such as straight flights with elevation changes and yaw changes. In addition, a novel path planning algorithm is implemented that additionally optimizes the quadrotor yaw and provides a framework for selecting the quadrotor among the swarm with the best path to a warehouse product.

2. Methods

This section details the materials and methods utilized to design an energy-aware path planning algorithm with a quadrotor for warehouse inventory management.

2.1. Design of an Energy Consumption Model for a Crazyflie Quadrotor

The Crazyflie, manufactured by Crazyflie, was used as the quadrotor in the study to perform inventory management [15]. The study restricts the major components to sensors and infrastructures from Bitcraze, including the Crazyradio

PA, which is responsible for interfacing the quadrotor with a desktop computer, and the Loco Positioning Deck and Nodes to localize the quadrotor.

The energy consumption model was designed to guide the path planning algorithm to generate paths that minimize the energy consumed by the quadrotor rather than minimizing the path length. The expected output from this model is a set of power equations, each corresponding to a quadrotor maneuver, as shown in Figure 1, as a function of velocity.

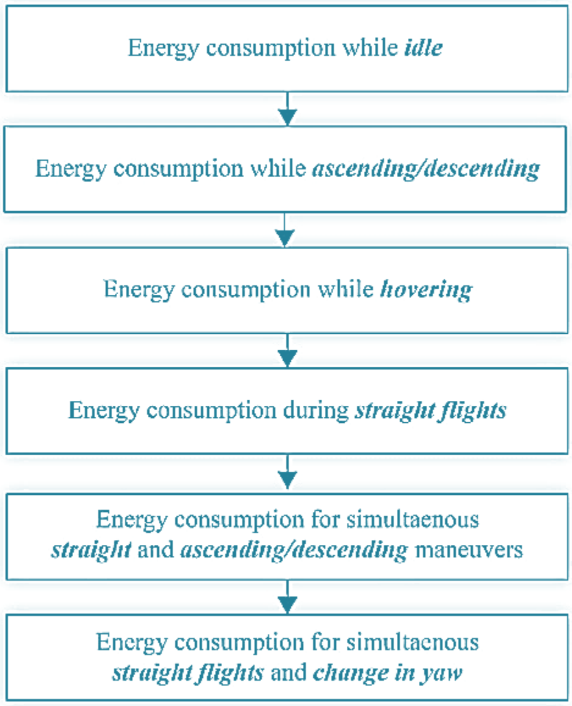

Figure 1. Quadrotor maneuvers for the energy consumption model

The quadrotor executes a trajectory at its fully charged state before it is connected to a charging outlet to record the energy recovered until its battery is full. In this case, the energy model assumes that the quadrotor is in full charge before performing the trajectory, as there are deviations in the recovered energy otherwise. The energy consumption of the quadrotor during its idle state is first recorded. For proceeding maneuvers, the energy consumption is based on the energy recovered subtracted from the energy consumed from other involved maneuvers, including the idle state. For example, a quadrotor should ascend first and descend after a flight to perform straight flights. The energy consumption for straight flights would be the total energy recovered subtracted from the energy consumed during the ascending, descending, and idle states. Different velocities were tested for each maneuver from 0.2 to 0.6 m/s, with 0.1 m/s intervals. A polynomial curve was used to extract the power equation for each motion. The energy equation is expressed as a product of power P, expressed in terms of velocity v, and change in time Δt (see Equation 1), which is used in the fitness function of the path planning algorithm to minimize energy consumption.

$$E = \int_{t_0}^{t_f} P(v)dt = P(v)\Delta t \tag{1}$$

2.2. Design of a Path Planning Algorithm for Automated Inventory Management

Among the evolutionary algorithms, PSO was used in the study of path planning algorithms due to the effectiveness of its variants. The algorithms tested for path planning are tabulated in Table 1, with acronyms that will be used to refer to these algorithms in the following sections. The CDPSO algorithm was designed in this study by combining the features of CPSO and DPSO, which served the same purpose in preventing premature convergence. All the variants were tested with 40 particles and 1000 epochs. Parameters such as inertial weight and acceleration coefficients were directly lifted from their respective studies. The SPSO parameters were copied from [14], and the parameters for CDPSO were taken from both CPSO and DPSO. These parameters were not changed to limit the number of tests performed for the path planning algorithm. However, changes in the values of these parameters would certainly skew the results. An image of the warehouse, the initial positions of the quadrotors, and the location of the good(s) to be scanned were used as inputs for the algorithm. Racks in warehouse environments are typically rectangular from the top view, so obstacles were assumed to be simple rectangles to reduce the computational time of the algorithm. Outlines of these obstacles were extracted with OpenCV, extending their outlines by 30 cm to provide clearance against collisions. The extraction of these outlines would not be representative of the obstacles if there were obstacles that cannot be simplified as rectangles, leading to nonoptimal paths.

Table 1. Parameters of PSO algorithms for path planning

Algorithm	Description	Parameters
SPSO	Standard PSO	$w = 0.729$, $c_1 = c_2 = 1.494$
CPSO	CIPSO without the last modification [13]	$w_0 = 0.9$, $w_1 = 0.4$, $c_1 = 3.5$, $c_2 = 0.5$, $V_1 = 0.5$, $V_2 = 0.1$
DPSO	CL-DMPSO [14]	$w_0 = 0.9$, $w_1 = 0.4$, $c_1 = c_2 = 1.494$, $m = 3$, $R = 5$
CDPSO	Hybrid CPSO-DPSO algorithm	$w_0 = 0.9$, $w_1 = 0.4$, $c_1 = 3.5$, $c_2 = 0.5$, $V_1 = 0.5$, $V_2 = 0.1$, $m = 3$, $R = 5$

Parameters: w inertial weight, w_0 and w_1 inertial weight limits, c_1 and c_2 acceleration coefficient limits, *V1* and V_2 maximum velocity limits, m subswarm size, and R regrouping period.

The position of the ith particle $\mathbf{P}_i$ for the PSO path planning algorithm is presented in Equation 2, where n is the number of intermediate waypoints, x, y, z refers to the quadrotor position in the space as Cartesian coordinates, and ψ is the quadrotor yaw. Clamped cubic spline interpolation was performed to connect these waypoints to ensure smooth motion of the quadrotor.

$$\mathbf{P}_i = [\mathbf{P}_{i1}, \mathbf{P}_{i2}, \dots, \mathbf{P}_{in}] = [(x_{i1}, y_{i1}, z_{i1}, \psi_{i1}), (x_{i2}, y_{i2}, z_{i2}, \psi_{i2}), \dots, (x_{in}, y_{in}, z_{in}, \psi_{in})] \tag{2}$$

The fitness function for the path planning algorithm is minimized mainly based on the quadrotor energy consumption model. As the algorithm is tailored for inventory management, objectives and constraints regarding quadrotor yaw rotations were included. The mean difference between the quadrotor yaw and heading was minimized to open up further applications for dynamic path planning where the quadrotor can use its onboard camera to detect obstacles along its path. The maximum yaw rate was added as a constraint, preventing the quadrotor from exceeding 90 degrees per second. In addition, typical constraints in path planning, such as environmental and interquadrotor collisions, were implemented.

The algorithms were then assessed for two warehouse layouts—traditional parallel and parallel with middle aisle layouts—referred to as parallel and middle layouts, respectively. Four quadrotors were placed along the four corners of the layout. A quadrotor is chosen, and a path is formed to reach a single product. For each layout and algorithm variant, 100 trials were performed to assess the algorithm. The performance metrics used to assess the generated paths are shown in Table 2. The main factors for assessing algorithm performance are the mean path energy consumption, yaw-heading difference, and computational time.

Table 2. Performance metrics for the assessment of the path planning algorithm

Performance metric	Unit
Energy consumption	Joules (J)
Yaw-heading difference	Degrees
Computational time	Seconds (s)

3. Results and Discussion

3.1. Design of an Energy Consumption Model for a Crazyflie Quadrotor

The power consumption plot of the quadrotor for common quadrotor maneuvers (hover, ascending, descending, straight) is shown in Figure 2. Idle and hover maneuvers were assessed as the average of ten trials, with the latter tested at different ascending and descending velocities. These maneuvers showed a linear relationship between energy consumption and duration, which denotes constant power with low standard deviations (see Table 3). In this study, the quadrotor ascended and descended at constant velocities. Thus, only the power incurred by the quadrotor at a speed of 0.5 m/s was recorded. Finally, the equation for straight flights approximately follows a quadratic relationship. The power initially increases as the velocity increases before dropping down once the velocity reaches higher values. The plot mirrors the tests performed by Di Franco & Buttazzo [8] at lower velocities, but the optimal velocity with the least energy consumption was not reached in the experiments.

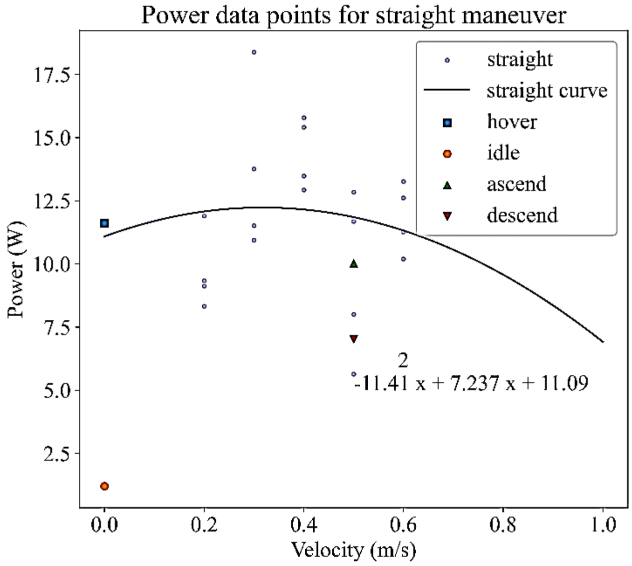

Figure 2. Power consumption plot for straight flight and other common maneuvers

Table 3. Mean power consumption and standard deviation of common maneuvers

Maneuver	Mean, *W*	Standard Deviation, *W*
Idle	1.2044	0.1754
Hover	11.613	0.727
Ascend	10.025	2.936
Descend	7.030	3.838

The power consumption for straight flights performed with upward velocities, downward velocities, and changes in yaw is presented in Figure 3. As illustrated in the figure, their energy consumption differences showed that adding ascending maneuvers would increase the energy consumption with velocity, as the quadrotor consumes more power to overcome gravity.

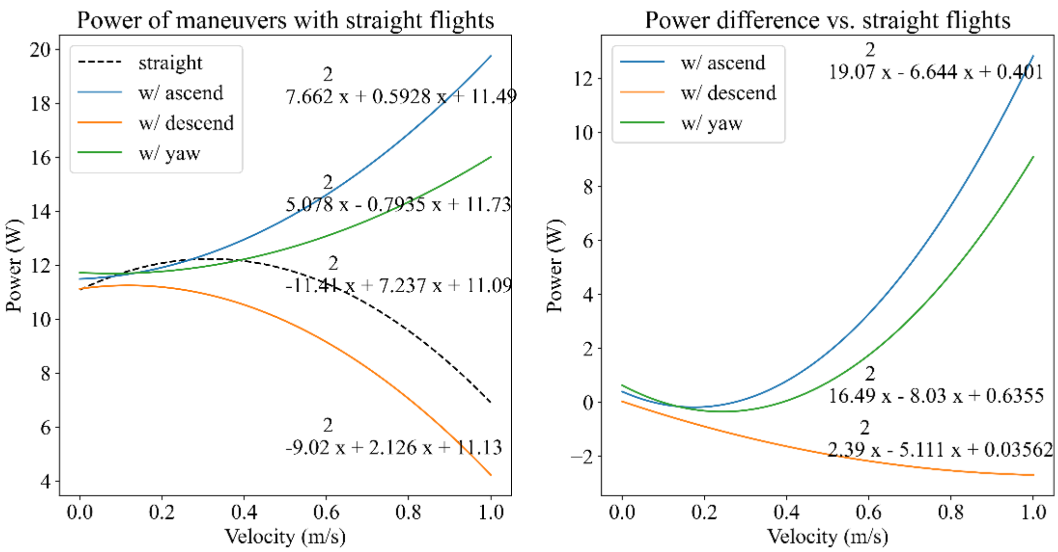

Figure 3. Power consumption plot for simultaneous straight flight and other maneuvers (ascend, descend, yaw)

The opposite is true for straight flights performed with descending maneuvers, as low downward speeds would need to generate higher lift to slow down the quadrotor's descent. When straight flights were performed with a change in yaw, the quadrotor energy consumption increased with straight flight velocity. Because it is desirable to determine the energy consumption in terms of the yaw rate, Equation 3 was used to represent the additional contribution of yaw to the quadrotor power.

$$P_{\text{yaw\_diff}} = 1.67060\theta^2 - 2.5567\theta + 0.64 \quad (3)$$

3.2. Design of a Path Planning Algorithm for Automated Inventory Management

The results of the path planning algorithm for all tested variants in the middle aisle layout are illustrated in Figure 4, where the energy consumption model is used as the primary objective. These results were compared to those of another set of tests for the same variants but with path distance as the primary minimization objective. The energy minimization objective had path distances comparable to those of the distance objective. However, the energy savings were significantly greater when energy consumption was minimized. The mean yaw-heading difference was also kept at a minimum (less than 90°) such that quadrotors with front-facing cameras would be able to react to obstacles in their path. Among the PSO variants tested, the designed CDPSO algorithm also had better paths based on the observed performance metrics. This was achieved with only slight increases in computational time; none exceeded 0.5 seconds.

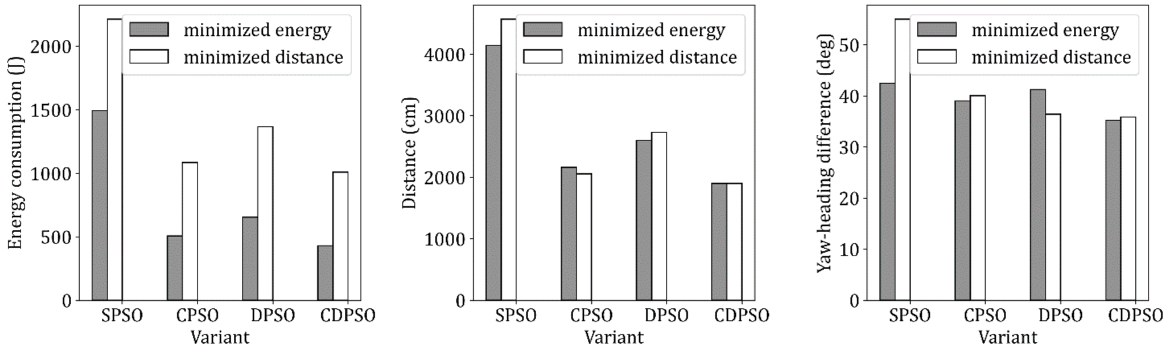

Figure 4. Parameters obtained for path planning in single inventory management for the middle aisle warehouse layout

The same observations can be observed when the algorithm is applied to the parallel warehouse layout, as shown in Figure 5. While the layout has more limited space for quadrotor movement, it has equal or lower energy consumption than the parallel layout. This can be attributed to the number of obstacles, with the middle aisle layout having twice as many obstacles, affecting the algorithm's convergence. With the consistent performance of the CDPSO algorithm in the two warehouse layouts, its effectiveness in path planning for warehouse operations was proven, especially when compared to other state-of-the-art PSO algorithms.

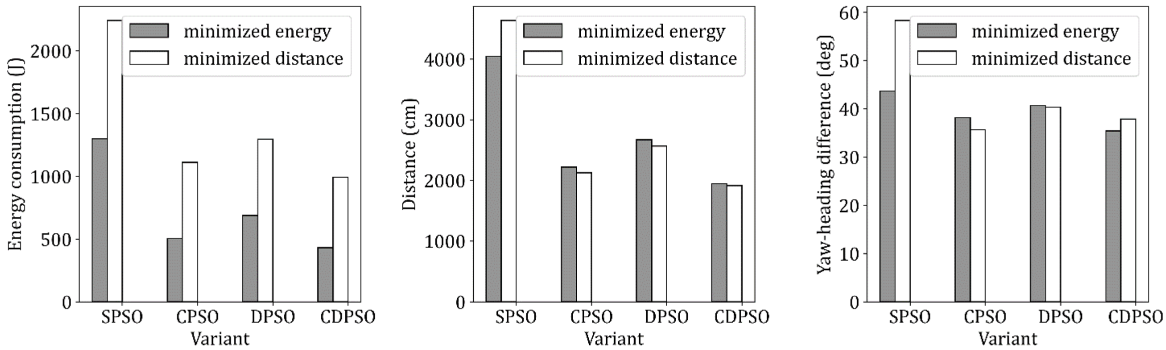

Figure 5. Parameters obtained for path planning in single inventory management for parallel warehouse layout

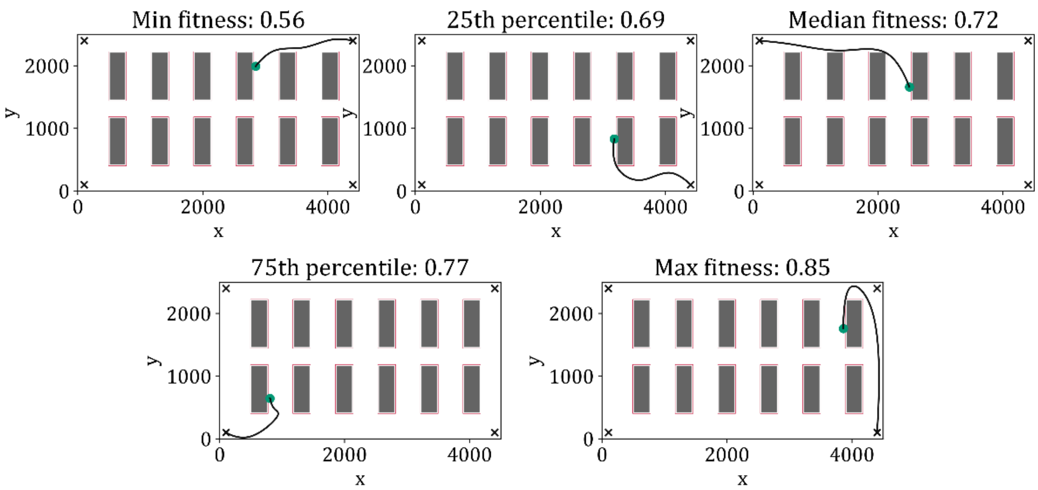

Figure 6. Paths generated by the CDPSO path planning algorithm for the middle aisle warehouse layout. One hundred trials were performed for the algorithm, and sample paths that obtained the minimum fitness, 25th percentile fitness, median fitness, 75th percentile, and maximum fitness values are displayed. The "x" symbols represent quadrotors, and the green markers represent the products.

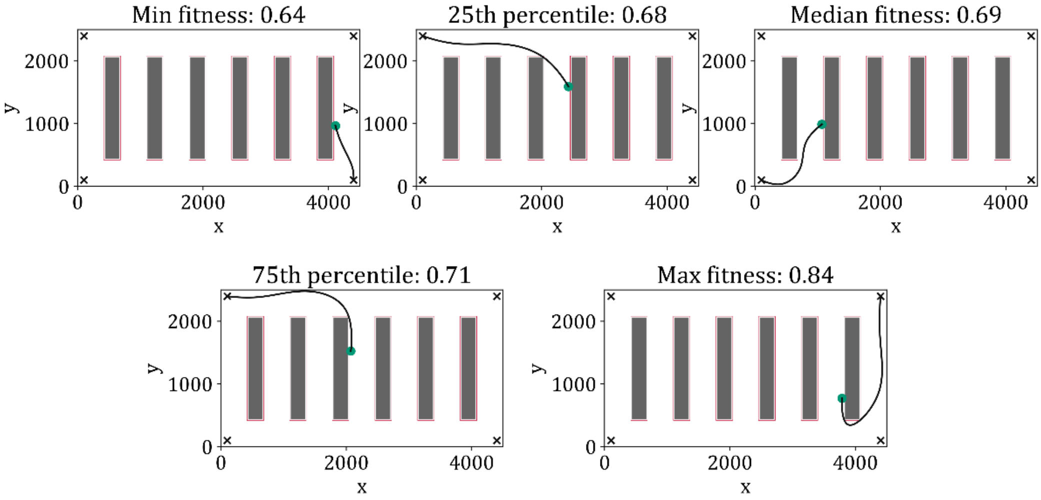

Figure 7. Paths generated by the CDPSO path planning algorithm for a parallel warehouse layout. One hundred trials were performed for the algorithm, and five sample paths with different values are displayed. The "x" symbols represent quadrotors, and the green markers represent the products.

The paths generated by the algorithm based on CDPSO minimized based on energy consumption are shown in Figures 6 and 7 for the middle and parallel layouts, respectively. For most of the illustrated paths, the nearest quadrotor to the task was chosen, except for the path with the maximum fitness due to restrictions added for maximum angular velocity. Moreover, the quadrotor tends to experience an initial ascent before descending to the task, which is likely due to the algorithm favoring energy savings from simultaneous straight and descending maneuvers.

3.3. Implementation of the Algorithm through Simulation

The simulations of the median paths obtained from the middle aisle warehouse layout were carried out using Crazyswarm. The difference in the paths between the simulation and algorithm outputs is illustrated in Figure 8, wherein it was kept below 2.65 mm at 95% reliability. However, the path with the maximum fitness had a distance error of 11.98 mm under the same conditions. Although the simulations were performed, the distance errors recorded were comparable to those of other studies, with [3] having a root mean square error of 18 mm and [4] achieving a mean error of 31 mm.

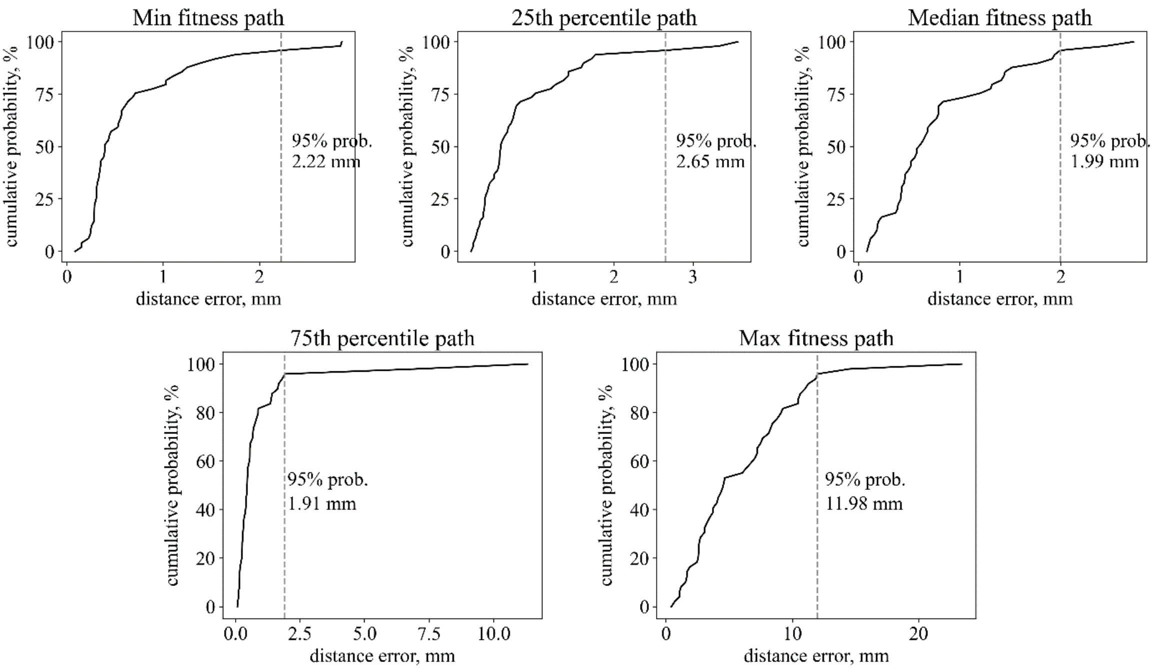

Figure 8. Cumulative probability plot for the distance error between the algorithm output and simulation results

This can be attributed to the longer computational time for trajectory conversion in the path with the maximum fitness, which had a longer flight time than the other paths. The slight difference between trajectories was also reflected in energy consumption, as presented in Figure 9, where none of the trials exceeded 0.6%. The model also achieved a significantly lower energy consumption difference, as low as 0.02%, for the path with the median fitness. These findings testify that the energy consumption model has a respectable accuracy in determining the energy consumed by the quadrotor when executing a given path despite having multiple maneuvers and yaw changes.

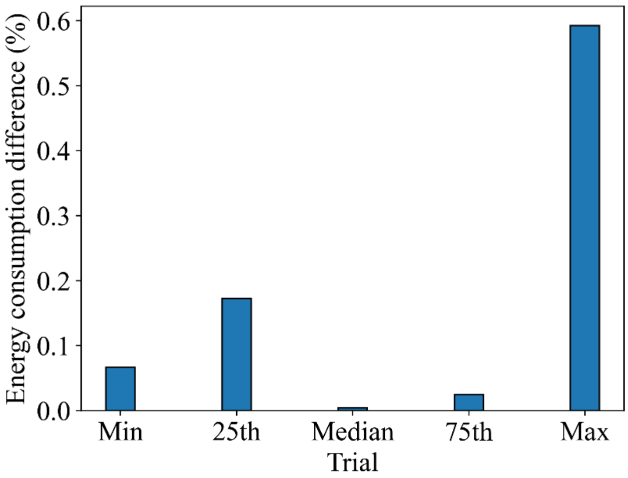

Figure 9. Energy consumption difference between the simulations and algorithm outputs. The x-axis is labeled based on which fitness value each trial corresponds to

4. Conclusion

The economic importance of efficient warehouse management calls for a system that can manage products situated in large spaces. UAV systems possess the capacity to fulfill this call; however, a common concern of UAV systems is the limited operational time due to battery constraints. This research addressed these concerns by developing an evolutionary algorithm based on PSO that is applied to a multiple-UAV system for warehouse management. The developed algorithm was evaluated against other models, and simulations were conducted with the developed algorithm. The results of these experiments showed that the path planning algorithm could satisfactorily perform inventory management in a warehouse environment. The energy consumption model establishes a relationship between energy consumption and quadrotor velocities for multiple maneuvers. The model optimized the distance and energy consumption of the paths generated from the path planning algorithm, with CDPSO consistently performing better than other state-of-the-art algorithms. Simulations verify the feasibility of the path planning algorithm, which reaches a maximum distance error of only 11.98 mm with 95% reliability and a 0.6% difference in energy consumption.

As the effectiveness of the path planning algorithm was proven for warehouse inventory management, future research can further verify the feasibility of the system with actual quadrotors in a warehouse. The effect of the localization system on the trajectories can be investigated. The energy consumption model can be further verified by comparing it with the energy the quadrotor recovers after it executes its trajectory. Future studies can also take advantage of the methodology used to construct an energy consumption model if the quadrotor does not directly measure specific parameters, such as the current. The CDPSO algorithm can be utilized in other path planning applications and improved to reduce computational time.

5. Declarations

5.1. Author Contributions

Conceptualization, C.D., A.C., T.C., and E.S.; methodology, C.D., A.C., and T.C.; software, C.D.; validation, C.D., A.C. and T.C.; formal analysis, C.D.; investigation, C.D.; resources, A.C. and T.C.; data curation, C.D.; writing—original draft preparation, C.D.; writing—review and editing, A.C., T.C., and E.S.; visualization, C.D.; supervision, A.C., T.C., and E.S.; project administration, A.C. and E.S.; funding acquisition, C.D., A.C, and T.C. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

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5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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