Optimized Drone Navigation: Integrating Neural Networks with Ant Colony Optimization for Precise and Fuel-Efficient Delivery Routes

Arnob Paul, Rafat Ferdaush
Dept. of Electrical and Electronic Engineering,
Shahjalal University of Science and Technology
Sylhet, Bangladesh.
arnob26@student.sust.edu, rafat59@student.sust.edu

Abstract

The study of sophisticated route-planning techniques is a result of the increasing demand for quick drone delivery services. This study introduces a novel method that blends neural network predictions and Ant Colony Optimization (ACO). ACO draws inspiration from the way ants use pheromones or smell trails to choose the optimal routes. This aids in determining effective distribution routes, as does the use of neural networks—computer models that learn from data. The affordability of the drone utilized in this study is an intriguing feature. With an Arduino Nano microprocessor and an MPU6050 gyroscope and accelerometer, the drone can fly steadily and affordably. Data from Google Maps is included into these routes to make them more useful. Roads, buildings, and shifting traffic patterns are examples of real-world difficulties that are considered. This method's eco-friendly approach is yet another important benefit. The drone minimizes its environmental effect while covering a greater area with less fuel thanks to its fuel-optimization system. This blended model's preliminary testing yields encouraging findings. This method provides higher fuel savings and faster delivery times than conventional routing approaches. This study offers a thorough analysis of this combination approach, emphasizing how it may become the new norm for reasonably priced drone delivery.

Keywords
Drone delivery services, Neural network prediction, Ant colony optimization, MPU-6050, Fuel-optimization system

Introduction
Conventional routing algorithms frequently produced inefficient pathways, which raised operating costs and prolonged delivery times. These algorithms have trouble scaling as the number of delivery locations increases, particularly in crowded metropolitan regions. It was difficult to adjust to shifting conditions, such as weather patterns or air traffic, and this frequently resulted in delays. Finding the shortest path between several locations required a lot of processing power due to its high computational complexity. Drone load balancing was ineffective, which resulted in unequal consumption and wasteful use of energy. Lastly, the inadequate management of time-sensitive deliveries by old techniques frequently affected customer satisfaction and increased the environmental effect of each delivery.

The proposed drone in this paper will give a thorough answer to earlier drone delivery problems by combining Ant Colony Optimization (ACO) and Neural Networks (NN). Even in dense metropolitan environments, ACO effectively optimizes multi-point distribution routes, significantly cutting operating expenses and delivery times while improving scalability. Because the paths are shorter and more direct, this optimization immediately contributes to energy efficiency and a less environmental impact. Utilizing historical information to apply NN for obstacle avoidance greatly improves the drone's safety and adaptability by enabling in-the-moment modifications to avert dangers and preserve flying stability. Furthermore, by utilizing past data to forecast delivery times, NN's scheduling accuracy is increased, resulting in more dependable service and higher customer satisfaction. In addition to improving delivery process efficiency overall, this dual strategy of ACO and NN also provides a greater level of safety and dependability, resolving many of the issues with drone delivery systems in the past.

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1.1 Objectives

The paper represents a unique approach using Ant Colony Optimization (ACO) and neural network predictions for effective route planning in drone delivery services. The drone described in the study can fly autonomously and is both economical and eco-friendly thanks to its MPU6050 sensor and Arduino Nano CPU. It describes an extensive technique that includes predicting delivery dates, neural network-based obstacle avoidance, ACO for optimum pathfinding, and hardware setup. According to the study, this integrated strategy offers notable advantages over conventional techniques in terms of fuel savings and delivery times, and it has the potential to set a new benchmark for drone delivery systems.

Literature Review

In the modern world, we are trying to do everything faster. Creating a shortcut path for making things faster is no different from that. Researchers have been working on this for a long time. The author of (Bander and White 1991) introduced a way called the "Route Optimization Algorithm". They introduced a heuristic search method, which finds optimum or nearly optimal pathways by returning a suboptimal option immediately and then converging to the best path if needed. It is intended for speedy decision-making in public transportation. Some researchers tried different ways of finding shortest path named the "Travelling Salesman Problem". It is a method that involves calculating the shortest path between an original city and a collection of supplied cities, making sure that every city is visited precisely once (Hoffman et al. 2013). The author of (Baita et al 1998) introduced a new method called dynamic routing which for some flexibility in the scheduling, loading, and routing of shipments. It manages the supply of commodities from different origins to different destinations while accounting for inventory and routing issues. Finally, the Authors of (Dorigo et al 2006) introduced a method called ant colony optimization. In this method, it tries to imitate how some kinds of ants forage for food. Pheromones left by these ants on the ground indicate advantageous routes, which other ants in the colony follow. ACO takes advantage of this technique to solve difficult optimization problems at their best by creating a virtual pheromone trail.

Using the Ant Colony Optimization (ACO) algorithm authors of (Huang et al 2019) are concentrating on solving the Feeder Vehicle Routing Problem (FVRP), a new variant of the vehicle routing problem where each customer is served by either a large vehicle (truck) or a small one (motorcycle). The objective is to minimize the total cost by determining the optimal number of dispatching sub-fleets and routes. By contrasting two distinct pheromone re-initialization strategies, the author (Brand et al 2010) examines the applicability of the Ant Colony Optimization (ACO) method to robot route planning in dynamic situations. The results are presented through computer simulations. In another research author (Zhang et al 2007) introduced an improved version of Ant Colony Optimization. That author presents two major enhancements to the Ant Colony Optimization (ACO) algorithm: an optimized implementation that drastically cuts down on the number of routings and running time, and the addition of individual variation that gives ants more options for routing strategies and accelerates the ACO algorithm's convergence.

For automated vehicle obstacles, avoidance is an important matter. To demonstrate the model's efficacy in path planning and obstacle avoidance, the author of (Glasius et al 1999) uses a topologically organized neural network of the Hopfield type with nonlinear analog neurons. Using neural network dynamics and activity gradients, computer simulations are used to show how quickly the system can provide an optimal path in environments with both stationary and moving obstacles. Using sonar and laser range finders for environmental data, this author (Chi et al. 2011) provides a neural network control system for directing mobile robots (AmigoBot and P3DX) through mazes with arbitrary obstacles, proving the system's efficacy in obstacle avoidance. To improve learning capacity and task completion in challenging circumstances, the author (Huang et al. 2005) describes an autonomous mobile robot obstacle avoidance technique utilizing a reinforcement learning neural network, especially Q-learning. To facilitate autonomous drone navigation in suburban areas, this author (Cetin et al. 2019) presents a deep reinforcement learning architecture that allows drones to recognize and avoid both fixed and moving objects. Using CNN for UAVs, the author (Back et al 2020) suggests a vision-based trail following method that is confirmed by simulations and real-world trials. The methodology of that paper focuses on obstacle avoidance, disturbance recovery, and preserving the UAV's location on the path.

There have been lots of developments in building affordably priced drones. Through clever adaptations of inexpensive mass-market technology, the author (Silvestro et al. 2019) hopes to create and execute accurate maneuvering solutions for tiny autonomous Unmanned Aerial Vehicles (UAVs), with a particular focus on overcoming the obstacle of restricted sensor and compute load owing to the UAV's lightweight. The author (Pütsep et al. 2021) seeks to overcome the absence of standard information across manufacturers by offering a thorough overview and explanation of the major parts of flight controllers for unmanned aerial vehicles. By optimizing an ultralight autonomous drone and switching from carbon fiber to printed circuit boards and 3D printed plastic, the author (Bigazzi et al. 2021) hopes to make it more user-friendly and versatile enough for a range of specialized uses, including precision agriculture, search and rescue, smart city management, and service robotics.

Methods

The method of building the proposed drone in this paper consists of four steps:

Hardware Configuration

The hardware of the drone is comprised of four 40000 rpm coreless motors with propellers for propulsion, an MPU6050 motion detection sensor, an NRF24 wireless communication module, and an Arduino Nano microcontroller for processing. Rechargeable batteries that are compatible with the power requirements and flying time of the motors power it. Electronic speed controllers (ESCs) regulate the motors' speed. The drone's structure is intended to be robust but lightweight. The Arduino Nano is equipped with specialized Python software that facilitates autonomy. This software includes PID control loops, NRF24 communication protocols, ant colony optimization for path shortening for multiple delivery ,forecasting delivery time and data processing from the MPU6050 sensor. These algorithms allow the drone to perform intricate tasks like obstacle avoidance, waypoint navigation, and stable flight without the need for human intervention.

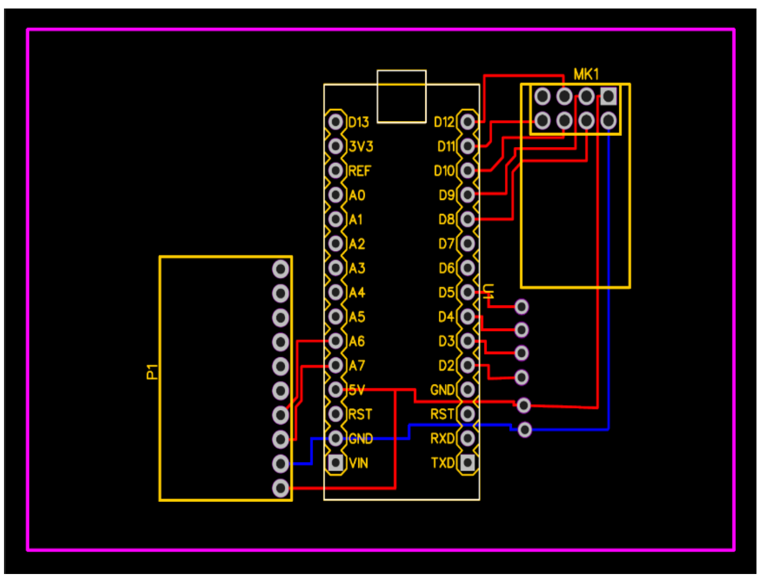

Figure 1. Hardware configuration of the drone

3.2 Ant Colony Optimization

In order to shorten the path for multiple delivery, ant colony optimization algorithm is used. There are many processes involved in utilizing Ant Colony Optimization (ACO) to determine the drone's shortest path. For this research nine delivery sites and one delivery hub is used.

Initialization: Each delivery point and hub is needed to be treated as a node in a network and their layout on a map is defined.

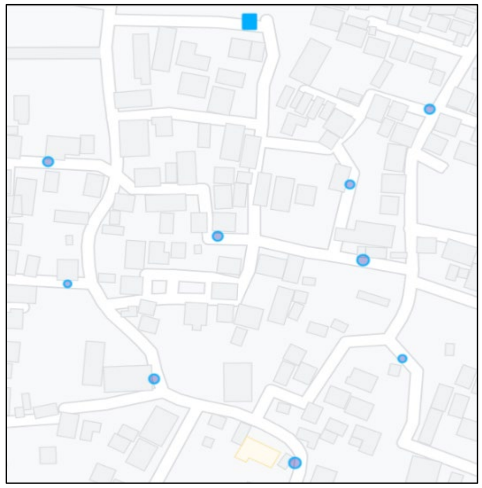

Figure 2. Network Map for Delivery points and Hub

Initialization of Algorithms:

Establishing the ACO framework is the first stage. As part of this, all pathways' pheromone levels are initialized with a notional value that represents an impartial preference in the beginning. 0.5 is chosen for the initial value of pheromone of all the delivery points.

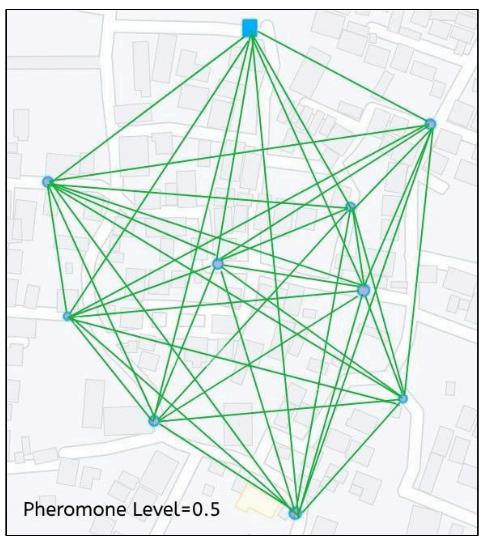

Figure 3. Initial Pheromone level configuration of ACO network

Ant Agents Building Solutions:

Ant agents are distributed from the hub, and they choose their own routes to destinations on their own. Pheromone concentration and a heuristic value (distance or time) determine the selection likelihood. Recurring node visits are prevented by recording the path history. For different distances, different level of pheromone is used. For example, for longer distances pheromone level is kept low to make sure the drone never follows that route. Similarly, for lower distances pheromone level is kept high so that the drone follows that route. Also, several delivery points is important. The pheromone value is inversely proportional to the number of delivery points in a single trip.

Considering these things, setting the initial pheromone value to [$\frac{1}{\text{Distance}*\text{Number of delivery points}}$] could be a decent place to start.

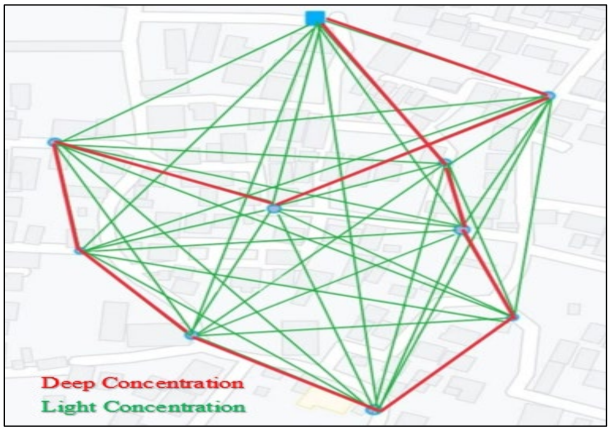

Figure 4. Pheromone level after first iteration

Mechanism of Pheromone Update:

Pheromone levels on routes are essential in ant colony optimization (ACO) for directing ants to discover optimum or nearly optimal solutions to a given problem. Once all the ants have finished their tours or traversals of the solution space, pheromone updates are usually carried out. Pheromone evaporation and deposition is the name of this process, which is essential to the ACO algorithm.

Let's dissect the ACO pheromone update's constituent parts:
Each ant leaves pheromone trails on the borders (paths) it has traveled after finishing its journey. The quality of the solution the ant encountered usually determines how much pheromone is deposited.
Pheromone deposition is commonly calculated as follows:

$$\Delta\tau_{ij} = \frac{1}{L_K}$$

Where,
$\Delta\tau_{ij}$= Amount of pheromone deposited on edge (path) ij &
L_k = Length (distance or cost) of the tour taken by ant k.

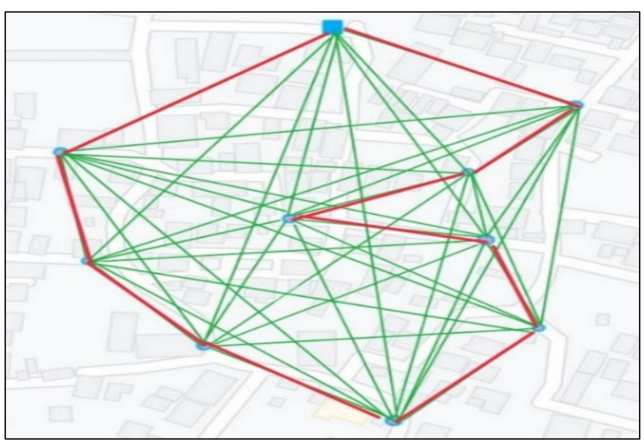

Figure 5. Pheromone update after 20 iteration

Evaporation of Pheromones:

There is a pheromone evaporation mechanism to guarantee the discovery of new pathways and prevent stagnation. Over time, pheromone on all edges progressively disappears. The rate at which pheromone evaporates is determined by the evaporation factor (ρ).

Pheromone evaporation is commonly expressed as follows,

$$\tau_{ij}\,(t+1) = (1-\rho)\cdot\tau_{ij}(t)\ ,$$

Where, τ_{ij} (t+1) denotes the pheromone level on edge ij at the subsequent time step. The pheromone level on edge ij at the current time step is represented by τij (t).

The evaporation rate (ρ) is a number that ranges from 0 to 1 that establishes the rate at which the pheromone evaporates.

Combining Deposition and Evaporation:

The deposition and evaporation processes are coupled in order to update the pheromone levels on edges. It is common practice to describe the total pheromone update equation for edge ij at each time step as follows:

The updated pheromone level on edge ij is denoted as:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\sum k\Delta\tau_{ij}^{k}$$

As of right now, edge ij's pheromone level is τ_{ij} (t). Its evaporation rate is ρ. The pheromone that ant k left on edge ij is called $\Delta\tau_{ij}^{k}$.

Convergence and Removal of Solutions:

Reaching convergence is a crucial goal. The consistency of the shortest path over several algorithm iterations is used to measure convergence. Drones search the solution space throughout each iteration, placing pheromones on edges according to the caliber of solutions they find. The method indicates progress toward a stable solution when it finds that the shortest path stays comparatively steady after several repetitions. The ACO system frequently uses techniques to exclude solutions with persistently lower pheromone levels to further improve optimization. In addition to encouraging variety, this elimination procedure frees the algorithm from being obsessed with less-than-ideal routes, allowing it to concentrate on optimizing and choosing the best routes for drone navigation.

Adjusting to Changing Circumstances:

Drone routing systems based on ACO perform exceptionally well in dynamic areas with variable circumstances. These systems use real-time data to easily adjust to shifting conditions. Understanding the present status of the environment is crucial, and it may be achieved by the continuous collection and analysis of environmental data, such as traffic patterns or weather conditions. The ACO algorithm can dynamically adapt heuristic values that affect path selection in response to these changes. For example, the system reduces the heuristic value of previously safe and efficient paths in reaction to increased traffic congestion or unfavorable weather. The algorithm can optimize routes in real time by giving priority to safety, efficiency, and timely delivery. This dynamic change of heuristic values also enables drones to navigate successfully in a constantly changing environment.

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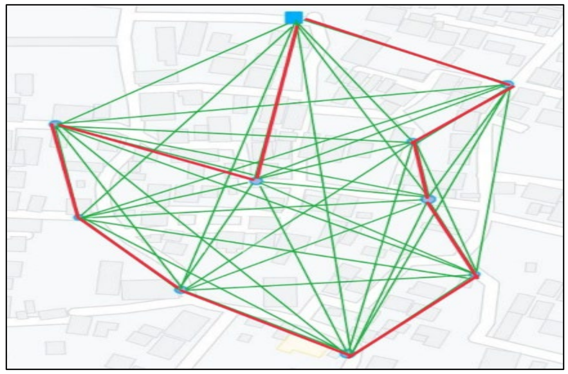

Figure 6. Pheromone level After Final iteration

To sum up, ants find effective routes with shorter trip lengths, and along these edges, their pheromone levels rise according to the quality of their solutions. In the meantime, evaporation causes all pheromone levels to progressively drop, encouraging ants to take detours and avoiding convergence toward less-than-ideal solutions. The ACO method relies on the equilibrium between evaporation and deposition to solve optimization issues effectively.

3.3 Obstacle Avoidance Using Neural Network

With a sonar sensor installed, the delivery drone was able to record its movements and interactions with obstacles for six months. The preprocessing pipeline included one-hot encoding of drone operations and normalization of sensor values to a [0,1] range. To validate and evaluate the model, the dataset was divided into a training set (20%) and a testing set (80%). Using Keras, a feedforward neural network with several hidden layers activated by ReLU, an output layer with a Softmax activation function, and an input layer matching the dimensionality of sensor data was created.

Initial tests were conducted to identify the hyperparameters of the model. Using a categorical cross-entropy loss function and the Adam optimizer, the model was trained on the preprocessed dataset. A confusion matrix, accuracy, and loss metrics on the testing set were used to assess the model's performance. The drone's onboard control system integrated the trained model to enable real-time data processing and decision-making. To evaluate the model's effectiveness in obstacle identification and avoidance, extensive field testing were carried out.

3.4 Forecasting delivery time

Using past flight and delivery data, the research created a neural network model to forecast the approximate delivery timeframes of an autonomous delivery drone. Over a predefined number of epochs, the model was trained using the Adam optimizer and the mean squared error (MSE) loss function. Metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were used to assess the model's performance on the test dataset. Real-time delivery time forecasts based on historical and present data were made possible by the integration of the trained model into the drone's navigation and control system. The accuracy and dependability of the model were guaranteed by the project's adherence to laws governing drone operations and data protection.

Data Collection

Two methods have been used to optimize the delivery process for autonomous drones: Ant Colony Optimization (ACO) algorithms and human shortcut path seeking. With the manual approach, human operators use their familiarity with the local topography and route-planning expertise to determine shortcuts for a predetermined delivery route. Nevertheless, there are drawbacks to this approach, namely its incapacity to fully optimize routes and consider all factors.

For the same predetermined delivery route, Ant Colony Optimization (ACO) is used to determine the best shortcut routes. The ACO system optimizes path selections based on distance and pheromone levels, simulating ant foraging behavior. In comparison to the manual method, the findings demonstrate that ACO regularly discovers shortcut pathways that are both shorter and more effective.

This next evaluation shows how an autonomous drone delivery system's obstacle handling efficiency improved over a few days. The system uses a machine learning architecture, gathers data on obstacle identification and management, and retrains itself on a regular basis. 7 days or 56 hours(8 hours per day) of visual obstacle avoiding data is collected using simulation. For the simulation, Airsim software is used.

The last evaluation is forecasting the delivery time. Using historical data drone estimates deliver time using neural network. Again, for data collection Airsim simulation software is used.

Figure 7. Using Airsim for Simulation

Figure 8. Drone navigation near high-rise building

Result and Discussion

A concrete illustration of ACO vs manual delivery was chosen, featuring a particular delivery path with several waypoints and possible detours. After the first iteration path created by ACO is 1.72% is longer than the human shortcut path seeking, as it takes 57 points to travel the full route created manually, whether it takes 58 points to complete the full route which was created by ACO. However, after 20 iterations, it takes 54 points to complete the full route which was created by ACO. Which is 5.26% shorter than the manual method. After 250 iterations, the path is no longer shortening. At the end, the path was 50 points long which is 13.79% faster than the manual method.

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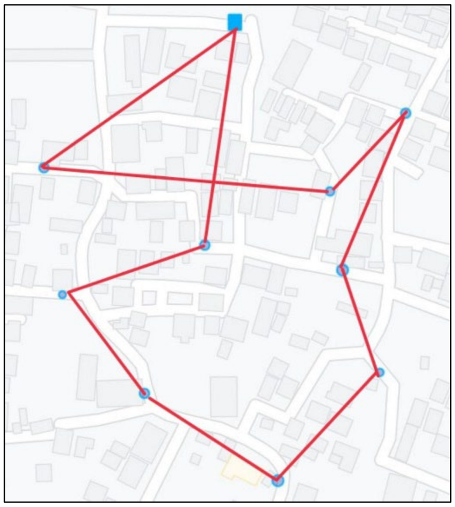

Figure 9. Shortest Path using manual method

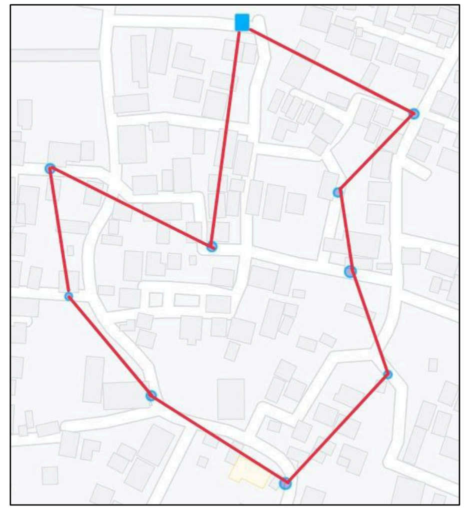

Figure 10. Shortest Path using ACO (Final Iteration)

As the drone is completing the full route in an average of 12 min 19 seconds, there were approximately 272 iterations in the simulation. Performance measures are kept track of, including detection accuracy, reaction speed, and success rate in avoiding problems. The effectiveness of the system is regularly assessed, and trends and enhancements are found through a longitudinal study.

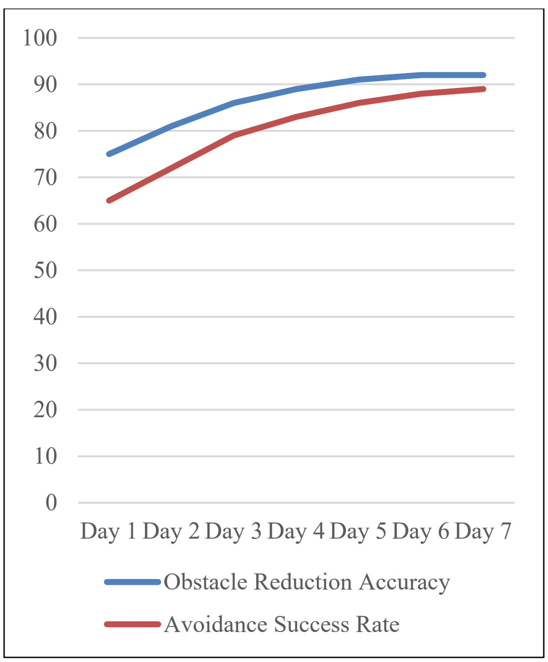

Figure 11. Obstacle avoidance accuracy

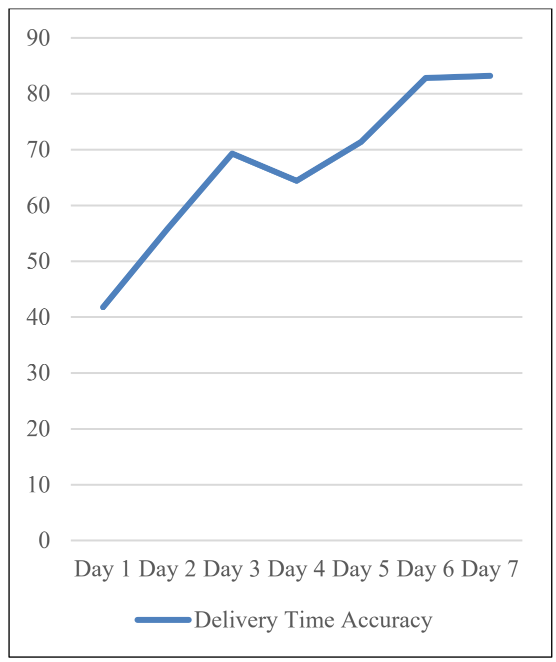

Figure 12. Forecasting delivery time accuracy

After 7 days of collecting delivery time data, to forecast delivery time, the efficiency is 83.21%.

Conclusion

The dual strategy of combining NN with ACO solves a lot of the problems that drone delivery systems have historically encountered. In addition to providing accurate delivery time forecasts, it optimizes routing, increases safety, and increases energy economy. Because of this, the solution not only increases the effectiveness of the delivery process but also provides a greater degree of safety and dependability, overcoming a number of problems that previous drone delivery systems had. The evolution of autonomous drone deliveries has advanced significantly with the combination of ACO and NN, offering more effective and environmentally friendly last-mile delivery options.

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Biographies

Arnob Paul, a passionate robotics and tech enthusiast, is pursuing a B.Sc. in Electrical and Electronic Engineering at Shahjalal University of Science and Technology. He has organized two major events and achieved an impressive 89% score in his PTAK Prize Supply Chain Analysis exam. Arnob has also made significant contributions to the field of robotics and tech, as a Mobile App Developer and Graphics Designer. He has won in competitions like Face The Case 3.0 and INIT 3.0, showcasing his technical and creative prowess. He has two Int. Conference papers on Papers: “A Comprehensive Android App based Solution for Automated Attendance and Management in Institutions Using IoT and TinyML”, “Design and Development of a Smart Agriculture (SA) System with Machine learning-based IoT Architecture”. His dedication to robotics and technology within Industrial Engineering and Operations Management is evident at the conference.

Rafat Ferdaush, a rising talent in Electrical and Electronic Engineering (EEE), is completing his B.Sc. in EEE at Shahjalal University of Science and Technology. His passion for programming, particularly Python, has led to the development of mini-games and a deep understanding of neural networks. Ferdaush's expertise in Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNN) has led to a deeper exploration of Convolutional Neural Networks (CNN). His speaker recognition software exemplifies his dedication to combining EEE knowledge with neural network principles. He is now exploring neuromorphic computing and spiking neural networks to explore their potential applications in electrical systems.

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