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A Delivery Time Reduction Heuristic using Drones under Windy Conditions

Abhishake Kundu, Timothy I. Matis
Department of Industrial, Manufacturing and Systems Engineering
Texas Tech University, Lubbock, Tx- 79409-3061

Abstract

In the domain of logistic operations, last mile delivery by Unmanned Aerial Vehicles (drones) has created quite a buzz recently. Considering that traditional truck delivery cost for "one minute per driver per day over the course of a year adds up to $14.5 million" [1], it needs to be ensured that the cost of setting up the infrastructure for deploying UAVs for parcel deliveries is offset by the time-money saved. Little research, however, has been conducted on the optimal routing and scheduling problem. A notable exception is the work of. Murray, et al. [2], who introduces the parallel truck and UAV Flying Sidekick TSP (FSTSP) model. In their work, it is assumed that the flight speeds are constant, yet this might be infeasible in practice when including the environmental effect of different wind velocities. In this paper, we consider the effect of wind and UAV battery-power consumption. The UAV is allowed to fly at certain airspeeds that optimize either airtime, distance flown, or power consumption. Experimental scenarios using different wind-velocities and number of delivery points have been simulated and the tour completion time metric is compared.

Keywords
Logistics; Heuristics; Unmanned Aerial Vehicle; Travelling Salesman Problem; Vehicle Routing Problem

1. Introduction

The all-pervasive potential of UAVs in the fields of defense, disaster management, aerial photography, 3D mapping, etc. is well documented [3]. One among these multi-faceted application of UAVs is 'last-minute' parcel delivery system, which when implemented in full bloom, can completely transform the way logistics industry operates. But there are operational and technical issues to overcome. One of the research works that addresses the operational challenge for deploying UAVs for parcel delivery system is the Flying Sidekick Travelling Salesman Problem Heuristic model proposed by Murray, et al. It is assumed that the UAV departs the truck at a particular node and then rejoins the truck at another node [2]. If either the truck or UAV arrives first to the rejoining node, the one must wait for the other. It is additionally assumed that the UAV may only carry one package at a time. One of the technical challenges of using a UAV, however, is battery life. The rate at which power is drawn, while in flight is a function of drag brought about by the aerodynamic structure of the UAV, with the primary variables of UAV payload and airspeed and velocity of the wind. This paper addresses this issue of routing the truck and UAV in an environment with a static velocity of wind and optimized airspeed, according to different objectives, using a variant of a route and reassign heuristic that is common in vehicle routing problems.

2. Physics of Drag

Carson [4] had shown that for small aircrafts in a no-wind condition, the Drag to Lift ratio (D/L) is given by the approximation

$$\frac{D}{L} = Av^2 + B/v^2 \tag{1}$$

where v is the flight speed and 'A' and 'B' are lumped parameters defined as $A\colon \rho(h)f/2W$ and $B\colon 2W/\rho(h)b^2\pi e$. Here, 'ρ(h)' is the air density at an altitude 'h' above ground, 'b' is the wing span, 'f' is the parasite area of the aircraft, 'e' is the Oswald's efficiency factor of the aircraft and 'W' is the weight of the aircraft (=mg). It is required that, to achieve a small D/L ratio at a given airspeed, both A and B must be small.

Nachmani [5] introduces a cost function for crossing an arc (i, j) assuming constant flight-speed. This cost function is the total energy spent (battery energy) by the aircraft engine in traversing from point 'i' to 'j'. It is given by:

$$\text{cost}_{ij} = \frac{DX_{ij}}{\eta} \tag{2}$$

where 'D' is the air drag, 'X_{ij}' is the distance covered in the arc from point i→j and 'η' is the constant engine efficiency.

When considering the effect of wind, the frame of reference of the UAVs velocity is affected by the wind velocity, and is denoted by the vector representation: $\overrightarrow{V_{ij}}=\overrightarrow{V_{rel}}+\overrightarrow{V_{wind}}$, where $\overrightarrow{V_{ij}}$ is the UAV velocity from the Earth's frame of reference (also called groundspeed), $\overrightarrow{V_{rel}}$ is the UAV velocity in the wind-field (also called airspeed), and $\overrightarrow{V_{wind}}$ is the wind velocity. The angles β and γ are the wind angle and the angle made by the arc $\overrightarrow{V_{ij}}$ with respect to the Earth's frame of reference respectively. The flight direction in the wind's frame of reference is denoted by the angle α. Inserting in Eq. (2), the optimized cost function for an UAV in a wind-field can be derived to be:

$$\mathrm{cost}_{ij}^{opt}=\min_{V_{rel}}\left[\frac{W X_{ij} V_{rel}\left[A V_{rel}^2+B/V_{rel}^2\right]}{\eta\left[V_{wind}\cos(\beta-\gamma)+\sqrt{V_{rel}^2-V_{wind}^2\sin^2(\beta-\gamma)}\right]}\right] \tag{3}$$

and can be optimized under the general constraints:

- airspeed V_{rel} is greater than a minimum UAV stall velocity V_{stall} (to overcome lift);
- airspeed V_{rel} is greater than the wind-speed component against its direction given by:
  - tailwind: $V_{rel} \geq V_{wind}|sin(\beta-\gamma)|$
  - headwind: $V_{rel} \geq V_{wind}$
- groundspeed $V_{ij} \geq V_{min}$ where V_{min} ensures a minimum allowed time required to traverse the arc;
- airspeed V_{rel} is lesser than V_{max} (the specified maximum allowable airspeed) and
- Energy consumed ('i' to 'j') $cost_{ij}^{opt}$ is less than 80% of total energy content in the battery modules.

Throughout this paper, the following UAV representative parameters are used: V_{min} = 5kmph, V_{max} = 100kmph, V_{stall} = 5kmph; air-density ρ(h) =1.15kg/ m^2, wing-span b=1.93m, parasite area f = 0.028m^2, Oswald's factor e = 0.7, engine efficiency η=0.7, and mass of UAV m= 5kg. The cost function of Eq. (3) has overall a higher energy consumption for headwinds as compared to tailwind, which is to be expected, and also that direct headwinds ($|\beta-\gamma|=\pi$) consume more energy than indirect headwinds ($-\frac{\pi}{2} \geq |\beta-\gamma| \geq \frac{\pi}{2};\ |\beta-\gamma| \neq \pi$). For headwinds in general, the arc cost significantly increases with the velocity of the wind. In addition, the cost curve at a fixed headwind speed is non-linear with V_{rel} (or airspeed) as there is an initial cost to overcome static drag and then to gain incremental thrust. A plot of Eq. (3) under differing wind scenarios is given in Fig. (1).

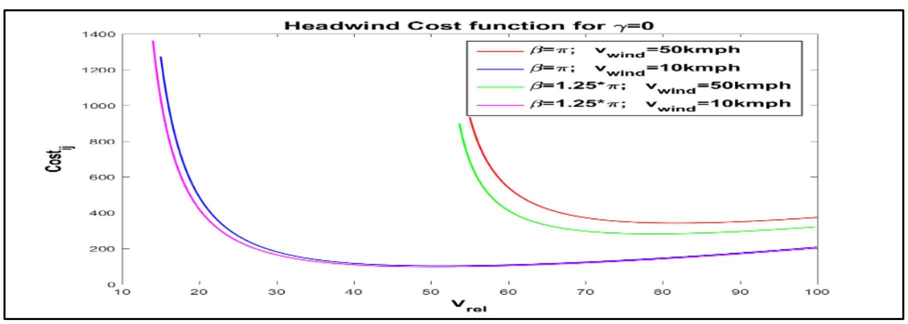

Figure 1: Headwind cases of light (10 kmph) and strong (50 kmph) velocities with different wind angles

3. Variable Performance Speeds

Erb [6] introduces three different types of speed performances for a small aircraft: maximum endurance, maximum range and maximum cruise speed, each having a particular objective with respect to the amount of power consumed.

The **'maximum range speed'** maximizes the distance traversed for per unit of battery energy consumed. This corresponds to the minimum airspeed (V_{rel}) for which the power over velocity ratio (P/V_{rel}) is minimum, or for which the drag force (D) is minimum, as shown in Figs. 2 (a, b). The **'maximum endurance speed'** of the UAV is the speed for which the amount of time in air is maximum for a required amount of fuel consumed, which occurs when the fuel flow is minimized for a particular airspeed (V_{rel}). This corresponds to the minima for the $cost_{ij}{\times}V_{rel}$ versus V_{rel} curve, as shown in Fig. 2(d). The **'optimum cruise speed'** is the UAV airspeed for which the fuel consumed per unit airspeed is the minimum. As noted by Carson [4], this airspeed is the "least wasteful way of wasting" energy, and occurs when $cost_{ij}/V_{rel}$ versus V_{rel} is minimized, as illustrated in Fig. 2(c).

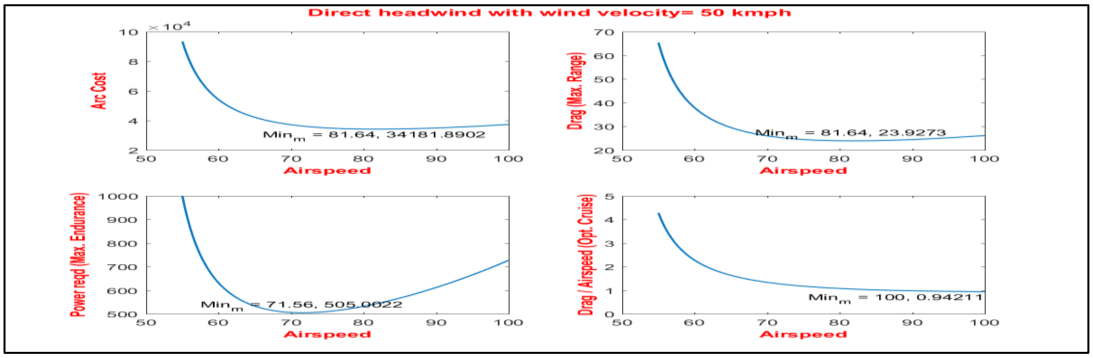

Figure 2: Plot of speed parameters for a direct headwind with γ=0, β= π, $V_{wind} = 50kmph$ and arc length X_{ij}=5km. From top-left clockwise: (a) $cost_{ij}$ versus V_{rel} (b) Drag ($cost_{ij} \times \eta / X_{ij}$) versus V_{rel}, (c) D/V_{rel} versus V_{rel}, (d) Power (D×V_{rel}) versus V_{rel}.

4. Implementation

The Flying Sidekick Travelling Salesman Problem assumes that there is a distribution center (the starting point denoted by node 1) from where the vehicles start and return. The truck and UAV may leave or return back separately or together from here. For every single delivery point that is visited by the UAV alone, the starting and ending node of the 3-node 'sortie' ('i' and 'k' nodes) is a truck delivered node. The middle node ('j') is where the UAV flies to deliver the package. Also, the points at which UAV leaves or returns back to the truck ('i' and 'k') are delivery points themselves (fulfilled by the truck) and the UAV and truck don't meet at any intermediate random location. When the UAV reaches 'k', the battery module is replaced and the time taken to do this is accounted as the recovery time (s_R), assumed to be constant 1 minute for all cases. Similarly, before launch from 'i', the delivery package is attached to the UAV, and this time, known as launch time (s_L) is also assumed to be constant 1 minute throughout. If the truck reaches point 'k' before the UAV, then it waits for its return, and similarly, when the UAV reaches 'k' before the truck, it hovers in its maximum endurance speed until the truck reaches the node 'k'. This effectively conserves battery energy preventing the UAV from crash landing. If the total energy consumption for flying from 'i' to 'j' and 'j' to 'k' and hovering at 'k' at 'endurance speed' (provided UAV reaches first) is less than 80% of the total energy available in the battery modules, then $< i, j, k >$ becomes an eligible sortie. It is to be noted that for any truck delivery points between 'i' and 'k' (inclusive), we cannot have any other $< i, j, k >$ assignments. But we can have node 'k' acting as the node 'i' for the next sortie or node 'i' being the return point ('k') for the previous UAV assigned sortie [2].

The heuristic has 8 functions inclusive of the main function. The X, Y coordinates of delivery points are a bivariate uniform distribution over a square region of 20 kilometers by 20 kilometers. Any number of delivery points can be chosen within this square region. We have a variable 'Cprime' that holds all the UAV eligible points [2]. 'WindCalculations' is a function that calculates the Euclidian distance matrix (for the UAV traversals), the Manhattan distance metric (for the truck traversal), the maximum endurance, maximum range and optimum cruise speeds for any given 2 points for a specific wind angle ($\beta = \pi$) and wind velocity. Another consideration, the fixed UAV air-speed [2], is checked for its feasibility. This function also calculates the time required for the truck and UAV (all air-speeds) to traverse any $< i, j >$. 'SolveTSP' function returns the node sequence and the arrival time at each node, starting and ending at the depot, for the traditional truck delivery problem. For this problem, we use a Genetic Algorithm to perform the computation. In essence, any tried TSP algorithm may be used.

Now, for each UAV eligible node, the associated time 'savings' is calculated using the 'CalcSavings' function. This savings is the time saved when the node is removed from the corresponding sub-route. The 'CalcCostTruck' function calculates the cost associated with inserting the specific node in the truck route between two adjacent nodes. If the sub-route considered has an UAV assignment within it, it needs to be ensured that the insertion of a node in the truck's path is still a feasible one, i.e., the UAV can still fly $i \rightarrow j \rightarrow k$ and has enough battery energy left to hover at the endurance speed at point 'k' until the truck arrives (provided the truck arrives later than the UAV). This total energy consumption must be less than the 80% of the energy available within the battery modules. In order to calculate the energy consumption, another function, 'EnergyCalc' is summoned. If the energy consumed is still feasible and the 'savings' associated with this node exceeds the 'cost', then an assignment update is performed. Similarly, 'CalcCostUAV' calculates the cost of serving the subject node using the UAV. For any 2 nodes 'i' and 'k', where, 'i' precedes 'k', the assignment is checked for the prospective $i \rightarrow j \rightarrow k$ sortie. Energy calculations are implemented to ensure that the UAV can fly the sortie and have battery energy left for hovering (when required). The 'PerformUpdate' function implements the changes required when an assignment is made. At the end of every iteration, for a unique subject node, the value for $'savings - cost'$ is checked if it is positive. Whenever it results in a positive value, the 'PerformUpdate' function checks if the new assignment is for an UAV or truck. It accordingly makes the necessary changes and updates the truck sub-routes and the time of arrival at each node.

5. Results and analysis

Scenarios with various number of delivery nodes, wind velocities and average UAV velocities were tested, keeping wind angle (β) as 180^0. The maximum UAV eligible payload was taken as 5 kilograms and the battery energy capacity per sortie was taken to be 250 Watt-hour (or 900 KJ), which is consistent with commercially available Lithium-polymer batteries [7]. The other parameters are held at those previously noted.

5.1 Illustrative Examples

In the following two illustrative examples, the scenarios of 1) truck only, 2) UAV with Optimum Cruise, 3) UAV with Optimum Range, and 4) UAV with constant airspeed are considered. The first scenario has a 30 kmph wind velocity and UAV airspeed of 40 kmph. The second one has an increased wind speed and the constant UAV speed is decreased.

Table 1: Input parameters and route completion times for the 2 scenarios

Parameters						Route Completion Times (in min)			
Scenario	# Nodes	Area (sq. km)	UAV airspeed	Wind Velocity	Truck Velocity	Truck Only	Optimum Cruise	Maximum Range	Constant Speed
1	20	20X20	40 kmph	30 kmph	40 kmph	140.27	132.01	117.09	125.35
2	20	20X20	25 kmph	40 kmph	40 kmph	150.3	137.92	124.46	???

A graphical representation of the routing for scenario 1 is given in Fig. (3). Note that solid lines represent the truck route and dotted lines represent UAV routes. If we take the UAV airspeed to be constant 40 kmph [2], the mission gets completed in 125.35 minutes, an improvement upon optimum cruise traversal. If we take the instance where the UAV flies at its maximum range speed, the sorties are: 1→11→7; 7→6→18; and 18→12→3, while the truck routes as 1→ 10→ 14→ 2→ 20→ 7→ 21→ 19→ 13→ 9→ 15→ 17→ 16→ 4→ 18→ 8→ 5→ 3→ 1.

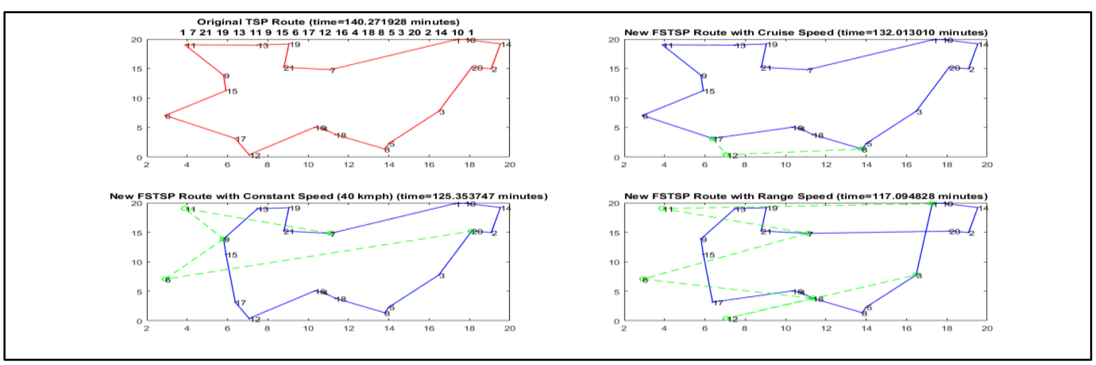

Figure 3: Scenario 1 Routing. From top-left clockwise: (a) Truck only, (b) Optimum Cruise, (c) Maximum Range, (d) Constant Speed

For a particular i→j, although optimum cruise speed travels at a faster velocity than the maximum range speed, the performance with maximum range speed is better because optimum cruise speed traversal for an arc consumes more energy, as compared to the maximum range traversal for the same arc. As the battery energy available for the sortie is a fixed constraint, it kicks in for majority of the sortie arcs, rendering the subject node to be UAV ineligible. Hence, overall time required to complete the assignment comes to be more in the case of optimum cruise speed traversals.

Fig. (4) shows the path allocation for Scenario 2. One interesting observation is that the constant UAV airspeed case (in the bottom left), shows no UAV assignments per se. This situation (for constant airspeed) arises due to the fact that given the constant airspeed value to be 25 kmph, it is much lower than the wind velocity (40 kmph), and hence this airspeed falls outside the feasible support of the possible airspeeds, so no UAV assignments can be made. The minimum feasible airspeed (V_{rel}) empirically calculated was found to be 40.33 kmph and the maximum was found to be 99.99 kmph. If the constant UAV airspeed was considered to be greater than 40.33 kmph, assignments would had been possible. Murray et al. considers a pre-defined constant UAV airspeed of approximately 25 kmph, 40 kmph and 55 kmph for the 72 test simulations that they ran [2]. The danger associated with these predefined airspeed values is that there may be cases where it wouldn't work, and would require a higher airspeed traversal, especially in scenarios where the UAV is being flown in a windy condition. In such a case, UAV assignments wouldn't be possible.

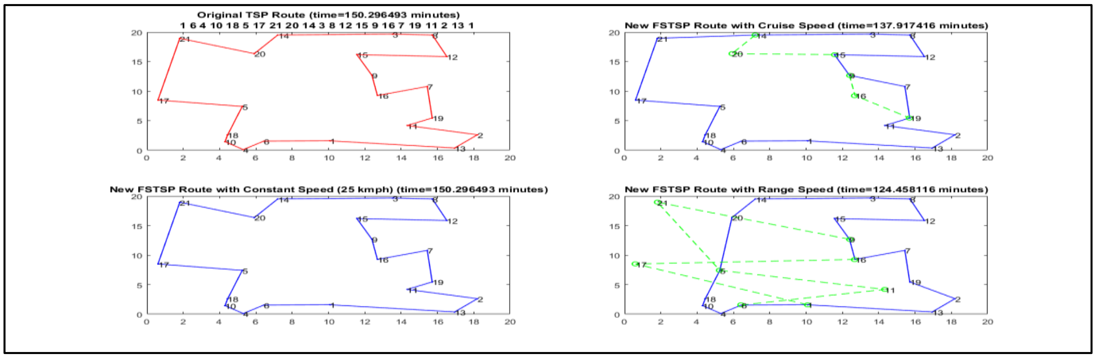

Figure 4: Scenario 2 Routing. From top-left clockwise: (a) Truck only, (b) Optimum Cruise, (c) Maximum Range, (d) Constant Speed

5.2 Simulation Experiment

This interesting observation led us to define a simulation experiment (in MATLAB) with 2 different factors (the number of nodes and the wind velocity) set at 2 different levels. The low and high levels for the number of nodes were set up to be 20 and 100 respectively, in the same square region. For the wind velocity, the lower and higher levels selected were 20 kmph and 50 kmph. For this 2^2 nested design, the responses that were recorded were the time to serve all the customers for the 4 cases: delivery using truck only, delivery considering a predefined constant UAV airspeed (40 kmph), delivery employing optimum cruise speed traversals for the UAV and delivery employing maximum range speed traversals for the UAV. Along with these responses, the computing time were recorded too. 100 simulation cases were run for each combination of factor and level, as shown in Fig. (5). Descriptive statistics for the average of these collected measures are given in Table 2.

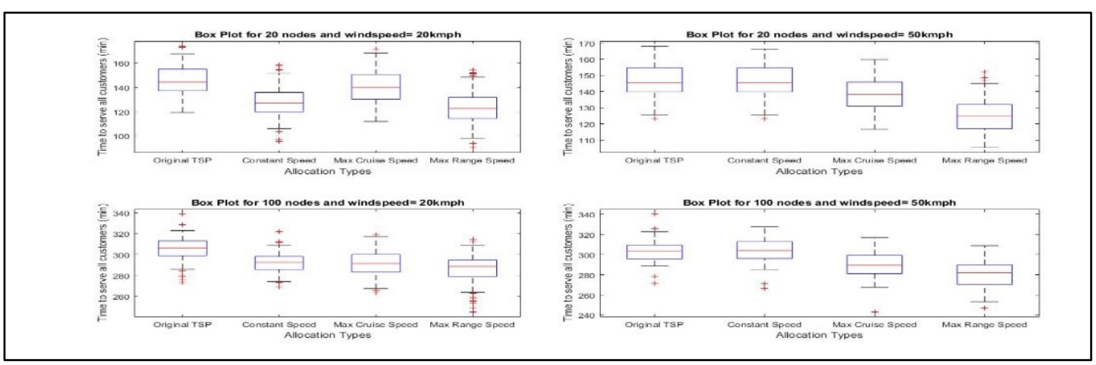

Figure 5: Box plots of route completion times with combinations of the number of nodes and UAV airspeeds

From the box-plots, it is evident that the scenarios employing maximum range speed for the UAVs outperform all allocation types. When the number of nodes considered is high, the maximum cruise traversal scenario performances slightly improves, but further analysis may be required. For the constant UAV airspeed allocation (40 kmph), the performance is better than optimum cruise speed allocation, but inferior to maximum range speed allocation, at a lower wind velocity level (20 kmph). When the wind velocity is set to the high level, the constant UAV airspeed case performs the worst, likely due to infeasibility over many of the routes. Interestingly, for higher number of nodes, the performance of a UAV at a constant airspeed is worse than using the truck only.

Table 2: Service time (in minutes) and computational time (in seconds) for the 4 allocation types

	Time to serve all customers (minutes)												Computation Time (seconds)								
	Original TSP (truck only)			Constant UAV airspeed (40 kmph)			UAV with optimum cruise speed			UAV with maximum range speed			TSP+ Constant airspeed (40 kmph)			TSP + UAV Optimum Cruise speed			TSP + UAV Maximum Range speed		
Allocation types	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum
20 nodes, V_{wind}= 20 kmph	145.52	119.29	173.96	127.86	95.35	158.74	140.65	111.94	171.89	123.76	90.26	154.15	202.25	124.73	304.16	201.65	135.13	286.28	200.92	162.24	284
20 nodes, V_{wind}= 50 kmph	146.36	123.22	168.03	146.34	123.22	166.26	138.74	116.7	159.77	125.11	105.32	151.97	179.38	172.97	213.18	179.24	148.06	206.48	178.27	71.69	205.95
100 nodes, V_{wind}= 20 kmph	305.04	273.58	338.93	292.52	268.98	322.14	291.74	263.36	318.67	285.62	244.89	314.99	364	142.89	5714.34	314	145.57	781.26	317.94	148.58	1072.59
100 nodes, V_{wind}= 50 kmph	303.78	271.77	340.33	304	266.52	327.53	289.89	243.01	316.75	280.87	247.04	308.79	355.56	178.44	4959.76	488.49	129.04	7179.04	415.91	163.94	8716.14

6. Conclusion and Future Research

This research looks at a modified route and reassign heuristic algorithm, as proposed by Murray et al [2]. Remodeling other evolutionary assignment heuristics and incorporating multiple UAVs [8] and trucks in the problem can be used to obtain lower bounds [9]. The physical possibility of implementation of diverse algorithms is immense operationally, but the biggest challenge lies in its technical implementation. Obstacle detection and avoidance, the ability to fly in windy conditions, constraints imposed by battery energy available per flight, the weight of the parcel, and safety issues related to securely dispatching and delivering parcels can be a few of the technical factors that come into play. A significant portion of the research looks at the various performance speeds at which the UAV can fly. Alongside this research, optimizing the UAV flight path itself, can also be looked at. A thorough experiment may be set up to compare the cost for changes in weight of the parcel or the changes in the available energy within the battery modules. Although 86% of deliveries made by Amazon weigh up to 5 pounds [10], the feasibility of carrying heavier parcels may also be looked at. This research considers a fixed air density (at the flight level) and wind-speed. What happens when these parameters change with respect to time? The heuristic can be modified and developed, where it may dynamically collect weather information from sensor data in a GPS-INS system, and would be able to plan the routing assignments in real time. Relaxing existing operational constraints and implementing rigorous technical constraints may change the whole dynamics of the original heuristic. But still the same question requires addressing: Is the cost for sophisticated technological implementation justified?

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