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Travel route and formation optimization for flocks of drones in package delivery by using an ACO based V-Shape algorithm

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ABSTRACT

Despite a lot of research throughout the last half century about the fact that geese and other bird species have the tendency to fly in a V-Shape configuration, investigation about applying this phenomenon to swarms of drones used in parcel delivery is limited. The extensive increase in online shopping and the resulting intensified package transport have urged the importance to optimize travel routes and swarms configurations in order to reduce the energy needed to carry out these tasks by the use of drones. To minimize the amount of energy needed by a swarm to travel an optimized distance, an Ant Colony Optimization (ACO) based V-Shape algorithm is applied on different configurations of swarms, each with a different drag coefficient, a distinctive surface opposite to drag, and a separate energy recovery parameter. For groups of up to 10 drones it is best to move in a V-Shape, being a 37.3% better configuration for 4 drones and 15.7% more efficient for 9 drones than the next best, being the vertical line formation. For larger groups of 10 drones or more, the vertical line becomes the most energy efficient being 22.3% more (energy) efficient than the V-Shape for 16 drones and 38.6% more (energy) efficient for 25 drones.

1. Introduction

Necessity is the best trigger for invention: a key example of this hypothesis is the way that e-commerce parcel shipping and supply chain is forced to evolve as a direct result of the rapid acceleration of online shopping. Although package delivery is known since ancient history, where the need to transport goods (and messages) across long distances led to the origination of basic courier systems, parcel distribution and delivery has tremendously increased over the last few decades [19]. Companies like FedEx, DHL and UPS have made it possible to transport goods all over the world in a time frame of one or at most a few days, by using cargo airplanes between large airport hubs and consequently by applying trucks for door to door delivery. With the quick and significant rise of the e-commerce business, next day deliveries are accepted as the new normal by the increasingly demanding customer [43]. While businesses like Amazon have been pioneers, more companies are focusing on direct delivery of goods traded online than ever before. The past decade has shown a big increase in the number of direct to consumer shipments of products and packages [41].

With the emerging e-commerce market and the increased number of deliveries as a result of that growth, several problems arise, which can be divided in three major groups: limited sustainability, increased fuel and labor costs and reduced customer satisfaction. The latter is caused by several factors, such as among other delivery at a wrong location, delivery of damaged packages, lost or stolen packages and delayed deliveries [22]. The last mile delivery accounts for between 41% and 53% of total supply chain costs. Factors like traffic congestion, complex routing, increased delivery in urbanized environments, the need for specialized vehicles or equipment and of course labor cost, all contribute to the high cost of the final stage of parcel delivery [12]. Finally, sustainability is becoming more and more important in the world and since almost all trucks need fuel to drive from door to door, the amount of CO_2 emitted is subsequently increasing [9].

In order to counter the mentioned issues, thus reduce costs, increase sustainability and customer satisfaction, especially for the last mile delivery stage, new solutions and innovations are needed. Therefore, retailers are investigating and testing new delivery methods like (i) the utilization of self-service lockers allowing customers to select the locker location of their choice as their parcel delivery address [46], (ii) delivery to cars or inside the house to reduce the number of attempts and to improve customer satisfaction, (iii) the use of autonomous vehicles driving on electricity [8] and finally (iv) the application of drones as means

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Table 1
Comparison table between our research on the V-Shape algorithm and the existing literature on ACO and the use of drones for package delivery.

Existing Literature	V-Shape paper
ACO limited to vehicle route optimization [17,31] [33,30] [50]	ACO based V-Shape algorithm for energy minimization in drone delivery
Drag reduction V-Shape limited to birds and small groups of planes [40,7] [21,11] [6,48] [29,25]	V-Shape of drones for drag reduction and energy minimization
Means for energy reduction in package delivery [46,8] [14]	V-Shape of drones for energy reduction in package delivery
No study on wind effects in drone flight [29,25]	Influence of wind on power need for drones traveling in a V-Shape

of last mile transport vehicle [47,26]. While the first two options focus mainly on improving customer satisfaction and minimization of unsuccessful trips, the latter two are aiming to minimize fuel consumption, CO_2 emission and labor cost by employing unmanned, self-governing means of transport and delivery.

In recent years, the development of new technologies in the domain of unmanned aerial vehicles has been extensive [2,1]. These UAV technologies were adhered to simplify and dehumanize inspection, search and rescue, agriculture and construction tasks [37,24,28]. To further enhance the quality and speed of these tasks, swarms (or flocks) of drones are used. Hence, a swarm of UAVs with a smart monitoring system can rapidly and reliably cover a large inspection area by utilizing several parallel operating drones [42]. While there are papers on route planning for drones for delivery purposes, both flying single [36] or in a fleet [49], none of them included the optimal configuration for energy efficiency in which these machines must fly via an optimized route. In this paper, finding the routes with the lowest energy consumption for flocks of package delivery drones and the optimal formation in which they need to fly to minimize energy used, will be the center of the research. Minimizing the energy results in lower utilization of fuel and labor costs. Furthermore, battery operated vehicles additionally reduce the CO_2 emission and limit the fuel needed to almost zero in the last mile delivery. This is the first paper to use an ACO based algorithm to determine the best formation in which a swarm of drones must fly via an optimized route to obtain the optimization goals described before.

As a basis for the development of our algorithm, we looked at how flocks of birds move in nature when traveling large distances in groups. They tend to fly in a V-Shape as this configuration shows to be the most energy efficient [11,48]. The drones used to transport goods show some similarities with birds, as they are small and don't have a large surface causing drag. As the birds switch places to distribute energy consumption during flight and reposition themselves for the same reason [6], this behavior can be copied to swarms of drones, especially the fully autonomous ones. The latter has a common objective, but use sensors and communication to position themselves within the swarm in an optimal way, just like birds do.

The novelties of this paper are: (i) the use of an Ant Colony Optimization (ACO) based algorithm - named V-Shape algorithm - to determine the best route and configuration in which a flock of drones should fly to minimize its energy consumption and, (ii) investigating the influence of wind direction, the number of drones in a flock and the change in organization of the drones in the flock on the energy amount needed to fly the optimized route.

2. Related work

The reason why birds are flying in a certain configuration or shape has been investigated since decades [11,48]. In the seventies of the past century, Gould and Heppner (1974) visually studied geese flying in a V-shape and concluded that the ideal angles of the formation, applied by the birds, ranged from 27.5 to 44.0 degrees. This was far more precise than in previous hypothetical models [21]. They further observed frequent position changes within the flock by filming flocks of geese in the air. Badgerow and Hainsworth (1981) linked the decision of the birds to move in this V-shape to the lower amount of energy needed to reach their destination, taking into account the way the birds are positioned within the flock [6]. In more recent studies, Seiler et al. (2003) and Bajec et al. (2009) confirmed the link between the tendency of animals to fly in a V-Shape configuration and the lower amount of physical effort needed by the birds in the configuration [40,7]. Academic research has moreover shown that hereby not only the shape in which the flock flies is important but also the exact position of the birds in the flock and the distance of each member to the bird flying directly in front and the one directly behind. In fact, according to Weimerskirch et al. (2001) the wake turbulence caused by the bird flying in front of another in the flock causes an increase in lift for the bird behind, on top of the reduction of drag, resulting in a lower energy need for the birds in the flock behind the leader [51]. Additionally, the role of the leader in the flock is investigated and as to be expected, the aspect ratio - among other less important factors - of the leader is playing a dominant role in the amount of increased lift [44]. As transport by air became more important, especially in the military domain and the parcel delivery business, where multiple aircraft can fly in formation over a longer distance, the research on configuration optimization has significantly grown. Bower et al. (2009) quantified the fuel burn reduction for a set of 5 airplanes in a V-shape, ranging from 4% when the planes fly with a tip to tip distance that equals 10% of the wingspan, up to 11.5% when the wings of the airplanes overlap by 10% of the total wingspan [10]. This is not only due to the increasing amount of lift due to wake vortexes [13] but also as a result of the drag reduction caused by the formation in which is flown. Hence, the surface exposed to the drag is changing with the shape of the flock and thus the amount of fuel needed to overcome this drag varies along with it [4,34]. A detailed explanation of the aerodynamics of even a single aircraft is highly complicated and therefore the investigation of the influence of the shape on the energy consumption is limited to the drag of the surface opposite to the wind [15]. In the last decade, the application of drones in multiple industries has become extremely important. Unmanned aerial vehicles (UAV) are applied in agriculture for herbicide spraying [28], to supervise borders or detect illegal actions like unauthorized logging (timber harvesting) [37] and in construction for the vertical transportation of materials [24]. Recently, door to door package delivery, as a direct result of online shopping, has gained influence and the turnover of this business is still growing [16]. The increasing amount of deliveries demands more frequent use of transport means, and thus results in much higher fuel consumption, and CO_2 emission. Therefore, the use of UAVs is highly promoted, especially for reaching urban locations where traffic jams are causing significant time loss, fuel consumption and engine emissions. In their paper, Chiang et al. (2019) discussed the potential of drones for improving the last-mile delivery of products to consumers, both from an environmental and an economic point of view [14]. The use of drones indeed reduces the need for fossil fuels and thereby the emission of CO_2. To further lower the amount of necessary energy to perform package deliveries, two additional actions can be taken, being route optimization to minimize the total distance traveled and flock configuration optimization to reduce drag and increase lift [29,25]. To minimize the distance to travel, behavior of animals in their natural habitat has been the basis of the development of theoretical optimization models. Examples are extensive: Artificial Bee Colony (ABC), Bacterial Foraging Optimization (BFO), Bat-Inspired Algorithm (BA), Fish School Search (FSS), Cat Swarm Optimization (CSO), Firefly Algorithm (FA) and many more. A well known and vastly studied example is the Ant Colony Optimization (ACO) model, based on the social behavior of the insects and their desire to bring back food to their nest via the fastest path [17]. Another type of optimization models based on flock behavior, are Particle Swarm Optimization (PSO) algorithms, finding their origin in swarm intelligence shown by geese, starlings and other bird species. [33] Among other applications, the ACO is applied to the Traveling Salesman Problem (TSP), in which the travel distance is minimized for a person or object moving along stopping places, back to its point of origin, where each location is visited exactly once [31,50]. Although the behavior of birds in a flock has been studied - such as leader and follower behavior, overall morphology - since the previous century [33,30], there has not been any research on the total energy consumption of flocks and the link to the shape they are flying in (see Table 1). However, the reduction of energy by flying in the most energy efficient shape while traveling the minimal distance can be seen as an optimization model.

3. Method

3.1. Configuration

Fig. 1 shows a configuration of customers that need to be visited by a flock of drones, loaded at a central hub, visited in a random order. Each customer is represented as *XX* (XX ranging from 2 to 11), while the loading point is indicated as *1*. The drones are traveling from the central hub via each customer, back to the central hub, via a random route (sequentially from customer 2 to 11).

To determine the optimal configuration for a swarm of drones flying the optimal route, an ACO based algorithm is used in which the pheromone amount is replaced by the energy level of the drone and the evaporation coefficient is changed by an energy recovery factor. This energy recovery factor is a representation of the positive effects that other parameters like wake turbulence have on the power needed to overcome drag. This algorithm is run consecutively for different configurations in which the flock travels, being: (i) in a straight vertical line (Fig. 6), so one behind the other for all drones, (ii) in a V-shape with one leader (Fig. 3), (iii) in a rectangular shape (Fig. 5), (iv) in a diamond shape (Fig. 4) and finally (v) on a horizontal line (Fig. 7) where all drones fly next to each other. Each type of structure has a different drag resistance coefficient C_W (see Table 3), a distinct surface A exposed to drag (see Fig. 17) and a separate energy recovery coefficient (see Table 3), resulting in different amounts of energy needed to travel the same distance but in a separate shape.

The flow diagram of the used V-shape algorithm is shown in Fig. 2 and will be further discussed in paragraph 3.5. The model is set up in

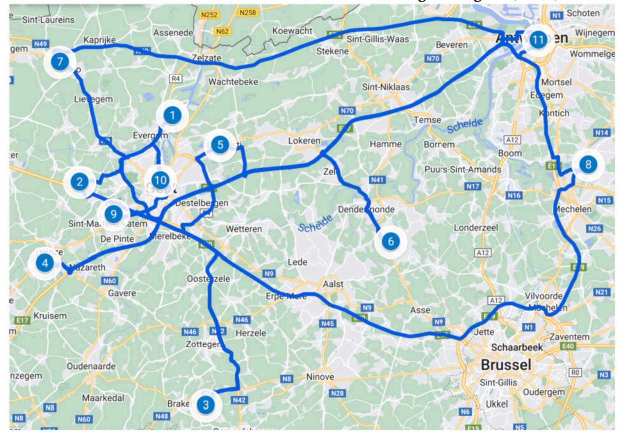

Fig. 1. Random route for a flock of drones.

such a way that it can easily be extended to a large variety of configurations, due to the fact that the input variables, like drag coefficients and energy recovery parameters, are set up as extendable arrays. The energy recovery parameter thereby includes all other parameters - like wake turbulence - delivering secondary lift (resulting in reduced energy consumption). It is thus a simplification of a set of very complex parameters into one concise variable.

3.2. Output parameters

The output parameters for the V-Shape algorithm are the amount of power (W) needed for the drones to overcome drag while traveling an optimal route, and the travel time relative to the reference V-Shape. Minimal power needed and corresponding relative travel time is calculated for all different shapes and for different wind directions. The values of all other configurations are compared to the travel time and energy value of the reference V-Shape. This comparison results in the identification of the optimal configuration (C) to be used in relation to the number of drones in the flock to minimize the energy consumption (see Figs. 12 to 16 and Fig. 18).

For example, if the optimal travel time - 1 kilometer equals 1 minute - calculated for a flock in V-Shape is 500 minutes and requires 300kW.min, then the same route flown by another constellation could take 700 minutes and demand 400kW.min, meaning that this flock needs 200 minutes and 100kW.min more to travel the same route in reference to the V-Shape. In other words, more energy for the same distance as the flock flying in V-Shape. In formula form, the travel time needed by the drones in the other configurations (D_o) relative to the travel time in V-Shape (D_r) is determined as follows:

$$D_o = \frac{C_{W_o} \cdot A_o}{C_{W_r} \cdot A_r} \cdot D_r \tag{1}$$

In which:

C_{W_r} = Drag coefficient of the V-Shape

C_{W_o} = Drag coefficient of the other Shape

A_r = Surface of the V-Shape flock exposed to drag

A_o = Surface of the other Shape flock exposed to drag

This formula is derived from the standard calculation in fluid dynamics of the drag experienced by a body when moving through a fully enclosing fluid [32]. In this calculation, the density of the fluid (ρ) and the speed of the body (v) are considered constant. The distance (or travel time) ratio of D_o versus D_r can then be written as the ratio of the drag forces for both configurations:

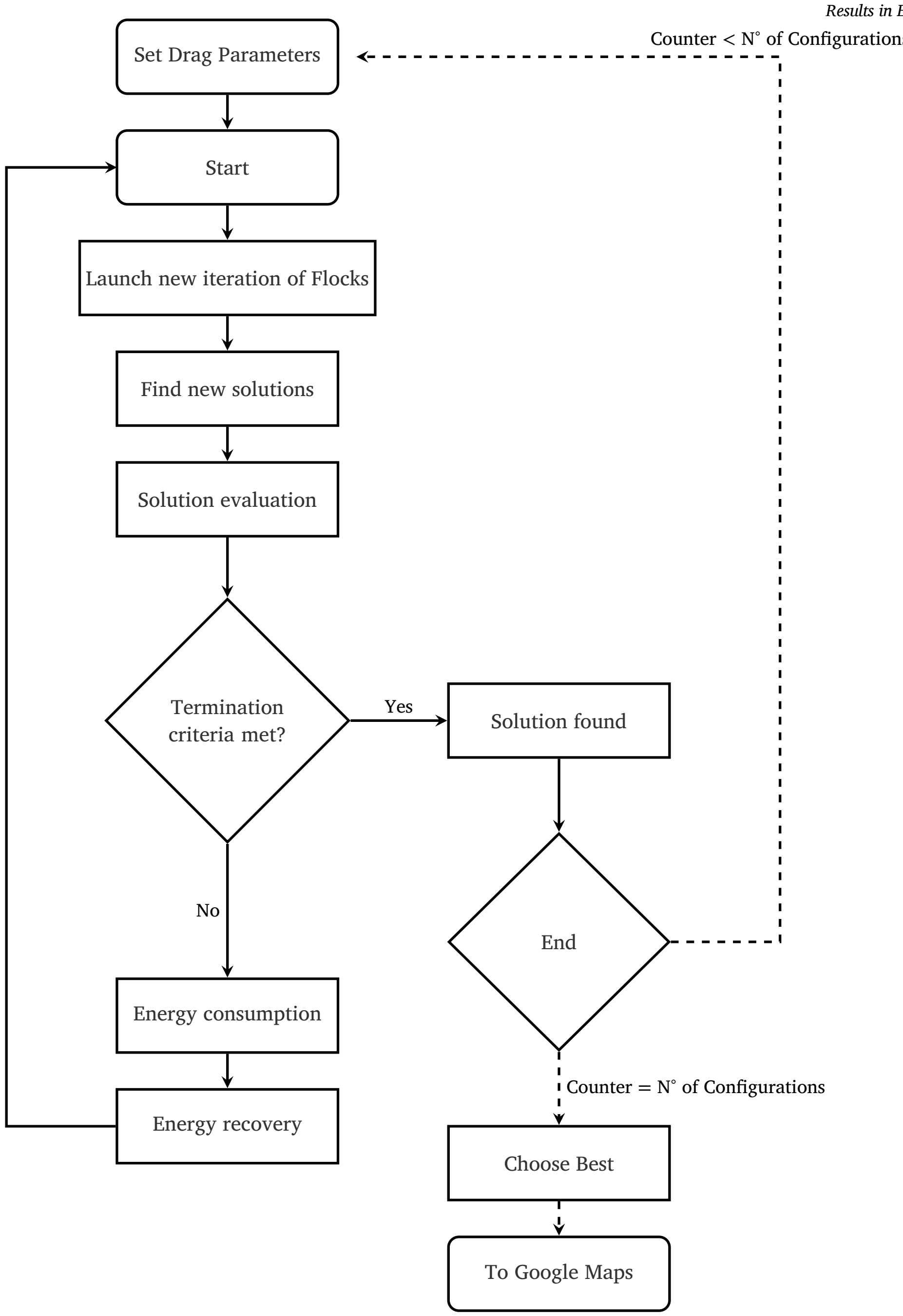

Fig. 2. Flow graph of the V-shape algorithm.

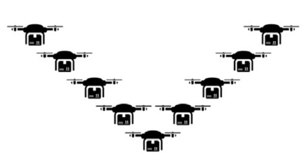

Fig. 3. Drones flying in a V-Shape configuration.

Fig. 4. Drones flying in a Diamond configuration.

$$\frac{D_o}{D_r} = \frac{0.5 \cdot \rho \cdot C_{W\,o} \cdot A_o \cdot v^2}{0.5 \cdot \rho \cdot C_{W\,r} \cdot A_r \cdot v^2} \tag{2}$$

Eliminating the constant values for (ρ) and v in nominator and denominator in Equation (2) results in Equation (1). The power that is needed by the flock in order to travel the optimal distance is calculated by using Equation (3). This formula exists of two parts, being first the power needed to overcome the drag force - calculated as the force multiplied by the speed [20] - divided by the energy recovery coefficient of the flock with a value between 0 and 1 as a first term. The second part of the equation implies the influence of the wind speed and direction on the total power needed. Headwind increases the power needed, tailwind

Fig. 5. Drones flying in a Rectangular configuration.

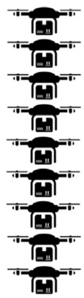

Fig. 6. Drones flying in a Vertical configuration.

Fig. 7. Drones flying in a Horizontal configuration.

reduces it.

$$W = ((\frac{0,5 \cdot \rho \cdot V_{sq} \cdot V_f \cdot C_{W\,o} \cdot A_o}{\theta_o}) - (0,5 \cdot \rho \cdot V_{sq} \cdot (\sin \frac{\psi}{2})^3 \cdot V_w \cdot C_{W\,o} \cdot A_o)) \cdot D \tag{3}$$

Where:

$\rho =$ Density of the surrounding air

$V_f =$ Speed of the drones in the Flock

$V_w =$ Wind speed

$V_{sq} = (V_f + V_w)^2$

$\theta_o =$ Energy recovery coefficient of the Flock

$\psi =$ The angle of attack of the wind

To compare the different flock configurations, the relative gain in power (ΔG_W) is calculated by dividing the power (W_o) needed by the flock in another shape (diamond, vertical line, horizontal line or square) minus the power needed by the flock moving in V-Shape (W_r), by the power needed by the flock in another shape:

$$\Delta G_W = 100 \cdot \frac{W_o - W_r}{W_o} \tag{4}$$

A second relative gain (ΔG_D) is calculated by dividing the travel time for another configuration minus the travel time for the flock traveling in V-Shape, by the travel time for another configuration:

$$\Delta G_D = 100 \cdot \frac{D_o - D_r}{D_o} \tag{5}$$

3.3. V-Shape - problem formulation

In the standard configuration (Scenario 0), we consider a flock of drones that needs to visit each customer exactly once to drop off packages and return to the home base afterwards (the central loading point). The delivery of the packages is done instantaneously and time frames do not need to be taken into consideration, except that each route of a flock needs to be completed in one day. The V-Shape algorithm can be solved to determine the minimal energy needed by the flock to travel the optimized distance in different configurations, being in a vertical line, a V-shape, a square, a diamond and a horizontal line. This is repeated for different wind speeds (from 0 $\frac{m}{s}$ to 5 $\frac{m}{s}$) and varying angles of attack of the wind, ranging from 0 to 180 degrees.

3.4. V-Shape - model

The Ant Colony Optimization (ACO) algorithm is a probabilistic meta-heuristic algorithm that is often used to solve complex combinatorial optimization problems [5,45,52,35]. The use of the ACO model is inspired by the behavior of a real ant colony, using their pheromone trails to find optimal solutions, thereby adding some artificial features, such as memory [23]. Ants communicate indirectly with the help of chemical pheromone trails, enabling them to find the shortest paths between their nest and food sources [3]. In the ACO algorithm, there is an interconnection between two solution techniques, being construction algorithms and local search algorithms. The construction algorithm technique builds the solution in an incremental way, by first creating an empty solution and then continuously adding suitable components until the complete solution is obtained. Local search algorithms will first generate an initial solution and subsequently search for a better solution in the neighborhood of the current solution space [38]. The ACO can easily result into a local minimum and can be time consuming to solve. To counter these disadvantages, every test was carried out ten times and a very powerful Apple M3-chip was used to perform the calculations.

The algorithm that we developed is based on the ACO, but instead of calculating the shortest path by following the trail with the highest amount of pheromones, the route with the lowest drag - thus needing the lowest amount of energy - is calculated and the pheromone evaporation coefficient is replaced by an energy recovery coefficient. The pseudo code of the algorithm can be written as follows:

procedure V-Shape Meta-Heuristic **is**
  while not terminated **do**
    generateSolutions()
    daemonActions()
    EnergyUpdate()
  repeat
end procedure

In the first step of each iteration in the algorithm, every flock generates a stochastic solution, i.e. the energy needed to fly a route (*generateSolutions*). It manages a group of flocks that concurrently and asynchronously move through neighbor nodes of the solution graph. In their movements, each flock applies a stochastic local decision policy, using both heuristic information and energy data. Thereby, the flocks incrementally build solutions to the optimization problem. Once a flock has created a solution - or while creating the solution - the flock evaluates the (partial) solution that will be used by the *EnergyUpdate* procedure to decide how much energy is needed. *EnergyUpdate* is the procedure by which the required energy is modified. The trails with lower energy levels will get a higher appreciation, while the energy recovery coefficient further improves the worth. The *DeamonActions* procedure is used to implement centralized actions that cannot be performed by a single flock, since they not possess the global knowledge.

Each flock needs to find a way to move through the graph. To single out the next edge in its route, a flock will take into account the drag of each edge accessible from its current position (node) and the corresponding energy (recovery) amount. At each step of the algorithm, each flock flies from node i to node j, corresponding to a more complete intermediate solution. The probability that flock f is moving from state i to state j $p_{i_j}^f$ relies on the combination of two parameters, being the attractiveness γ_{ij} of the move and ϵ_{ij}, the energy left behind by the flock when moving from node i to j. In short, the probability that the flock moves from node i tot node j is [39]:

$$p_{ij}^{f} = \frac{(\epsilon_{ij})^{\alpha}(\gamma_{ij})^{\beta}}{\sum_{k\in allowed_j}(\epsilon_{ik})^{\alpha}(\gamma_{ik})^{\beta}} \tag{6}$$

In which:

$0 \le \alpha$ parameter to control ϵ_{ij}

γ_{ij} typically equals $\frac{1}{d_{ij}}$, d_{ij} = distance between i and j

$0 \le \beta$ parameter to control γ_{ij}

γ_{ik} and ϵ_{ik} are values for all other branches

The energy level is updated after the passing of all the flocks at an edge between nodes i and j. In the following equation, θ represents the energy recovery coefficient, ϵ_{ij}, the energy needed by the flock when moving from node i to j, n is the number of flocks and finally $\Delta\epsilon_{ij}^{k}$ the energy left behind by the kth flock.

$$\epsilon_{ij} \quad \leftarrow \quad (1-\theta)\epsilon_{ij} + \sum_{k}^{n} \Delta\epsilon_{ij}^{k} \tag{7}$$

$\Delta\epsilon_{ij}^{k}$ can be defined by equation (8), in which D_k typically is the distance traveled along the edge for i to j and S is a constant. In this paper, S will be considered equal to 1, while D_k equals the relative distance, defined by equation (1).

$$\Delta\epsilon_{ij}^{k} = \begin{cases} \frac{S}{D_k} & \text{if flock k uses this edge in its route} \\ 0 & \text{in all other cases} \end{cases} \tag{8}$$

In the classic ACO algorithm the distance between two delivery points is taken from the distance matrix in which each value is calculated by using the Google Maps API. When running the V-Shape algorithm, the route calculation is done, based on the relative distance as described in Equation (1), that thus depends on the drag coefficient of the different configurations. The route distance for the minimal energy path is the one calculated for the reference configuration - in this paper the V-Shape - while other path distances are relatively longer (needing more travel time) for higher drag configurations (e.g. the horizontal line) and shorter for lower drag configurations.

3.5. V-Shape - solution method

The calculation of the route to be traveled by a flock of drones and its optimal configuration, with the least amount of energy needed to overcome the drag, can be done by solving the V-Shape algorithm. An ACO based algorithm is used where the pheromone amount is replaced by the energy consumption, the evaporation coefficient is changed in an energy recovery coefficient and the route is optimized, based on the required energy. In a first phase, this ACO based V-shape algorithm is calculated for the reference configuration, being the V-Shape, resulting in an optimal route with minimal energy need to overcome the total length of this route. Second, the same energy consumption algorithm is ran for four different configurations, being: (i) all the drones in the flock flying in a vertical line, so one drone directly after the other, (ii) the drones flying in a square shape, (iii) the flock moving in a diamond shape, and finally (iv) all drones on a horizontal line, so one next to the other.

The V-shape algorithm used is schematically shown in Fig. 2. In the outer loop the parameters of the flock configuration are set, being the drag coefficient C_W, the energy recovery coefficient θ and the surface of the flock subject to drag (A). After these values are set, the inner loop will determine the minimal energy route. Once the optimal solution is reached, the inner loop will come to an end and the result is obtained. This final step of the inner loop (Fig. 2) is then followed by a new outer loop where the next configuration parameters are set and the process is repeated until each configuration generates corresponding outcomes and the best configuration - with minimal power need - can be chosen. It is clear that each inner loop thus leads to an optimal energy consumption route - and relative distance - in reference to the V-Shape configuration, chosen as the reference form. This process, by determining the optimal configuration flying the optimal routes, is repeated for different amounts of drones in a flock - varying from 4 to 36 units - and for different angles of attack of the wind. The goal is to determine whether the number of unmanned aerial vehicles in a flock and the direction of the wind play a role in choosing the optimal arrangement of the drones in the flock when flying from point A to point B.

In the result section, we will discuss the use of the V-Shape algorithm to find the minimal energy route for all configurations, and by comparing all results, determine the configuration - shape and size - with the least amount of energy lost. The objective thereby is to obtain the lowest energy routes for each configuration and wind direction out of a vast set of possible solutions.

Table 2
Parameters.

Input Parameters	
N	number of drop off locations
C_{Wi}	drag coefficient of configuration i
C_{Wr}	drag coefficient of the V-Shape configuration (reference)
A_i	surface exposed to drag of configuration i
A_r	surface exposed to drag of the V-Shape configuration (reference)
V_f	speed of the drones in the flock
V_w	wind speed
ρ	density of the surrounding air
ψ	angle of attack of the wind
θ_i	energy recovery coefficient of configuration i
LL	set of coordinates of each drop off location
H	warehouse location
t_{ij}	travel time between two customers or between customer and warehouse
d_{ij}	travel distance between two customers or between customer and warehouse
W_{ji}	the power needed by a drone j in configuration i to travel the total distance
Decision variables	
N_{Si}	a sequence of package drop off locations for a configuration
F_{Ti}	total relative distance covered by a flock flying in configuration i
W_{Ti}	the power needed by a flock in configuration i to travel the total distance
Objectives	
Min F_{Ti}	
Min W_{Ti}	

3.6. Parameters

The parameters in this paper are divided in three main groups: (i) the input parameters are all known data before solving the problem, such as the location of each drop off point, the drag coefficient C_W of the flock configuration, the flock, the starting and ending point of each route, (ii) the outcomes of each run of the inner loop calculations are defined as the decision variables. These iterations stop when the objectives are met, (iii) these objectives form the final parameter category. See Table 2.

3.7. Scenario

As discussed, the goal of the V-shape algorithm is to determine an optimal route and the configuration that needs the least amount of energy to travel a route and thus to overcome the drag. As a result, it is determined which route needs to be followed by the group of drones - varying in numbers - flying in the best configuration for the total distance of the route. In the result section, the optimal routes with minimal

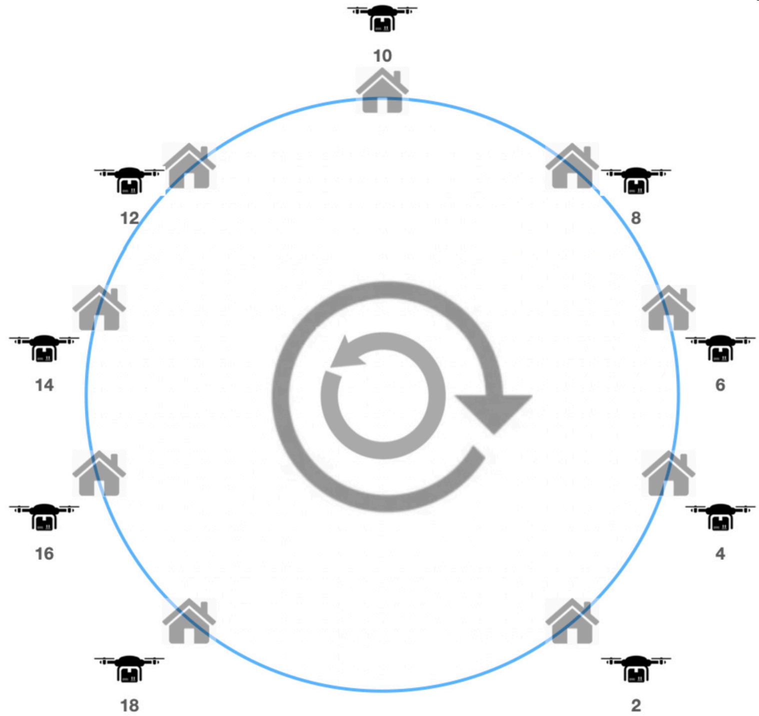

Fig. 8. Scenario 1 - Drones are left behind two by two at every customer and picked-up again when returning to the depot.

amount of energy (and relative distances) needed to travel these paths are listed for various configurations, with different numbers of drones (from 4 up to 36) and varying angles of attack of the wind (from 0 tot 180 degrees).

The solutions obtained in this first phase are then applied to specific scenarios in which the whole route is not flown in the same configuration. More specifically, we consider a flock of 18 drones that needs to visit exactly 9 customers, each at a distance of 10 kilometers from each other. Packages are assumed to be so heavy that two drones are needed to carry them. In a first scenario - shown in Fig. 8 - the initial flock exists of 18 drones and at each customer two of the drones stay at this location, while the rest of the flock continues its route - in V-Shape or in a vertical line - until at the last point only two drones are left.

According to Markets and Markets, drones will take over package delivery for parcels lighter than two kilograms over the next decades [27]. In these scenarios however, we wanted to investigate what to do with larger packages, requiring more drones to carry them. The energy consumed per drone flying from the start to the first customer, is the total amount consumed by this flock and configuration divided by 18 drones (the number of drones in the configuration up to the first customer) and multiplied by two, since two drones remain at the first location. Between Customer 1 and 2, the total energy needed by the flock is then divided by 16 - since only 16 drones fly from customer 1 to 2 - and multiplied by 2. This continues until the end of the route where only 2 drones are left. The total power needed by the whole flock is thus calculated by the formula in Equation (9).

$$W_{Ti} = 2 \cdot \left(\sum_{k=1}^{9} E_k^i \cdot d_{1k}\right) \tag{9}$$

In which:

E_k^i = Energy need by the flock moving to customer k in configuration i

d_{1k} = Distance between the start and the location of customer k

k = Number of drop off locations

Fig. 9 shows the second scenario, in which the complete flock will fly the whole distance of 100 kilometers in both a vertical configuration - one drone behind the other - and second in the V-Shape configuration. As we consider the drop off points dispersed in a circle, the total power needed by the group of drones in scenario two W_{Ti} will be the energy calculated for the total flock E_{Ti}, multiplied by 100 kilometers (Equation (10)), while the total amount of power calculated in scenario one needs to be doubled, since all pairs of drones need to be picked up again (Equation (9)).

$$W_{Ti} = E_{Ti} \cdot 100 \tag{10}$$

Finally a third scenario is studied in which two flocks of 9 drones fly in V-Shape or a vertical line at each side of the circle and return through the middle in straight line as a group of 18 drones, as shown in Fig. 10. The total power needed by all drones in this configuration is calculated by Equations (11) and (12), in which $E_{T_s}^{9}$ is the total energy required by a flock of 9 drones in a straight vertical line (Equation (11)) and $E_{T_v}^{9}$ is the same but for a flock flying in V-Shape (Equation (12)). This energy value is multiplied by half the interference of the circle, being 50 kilometers. In part two of Equations (11) and (12), the total energy required by a flock of 18 drones in a vertical line configuration $E_{T_s}^{18}$ is multiplied by the center line of the circle via which the whole flock of 18 return.

$$W_{Ti} = 2 \cdot (E_{T_s}^{9} \cdot 50) + (E_{T_s}^{18} \cdot \frac{100}{\pi}) \tag{11}$$

$$W_{Ti} = 2 \cdot (E_{T_v}^{9} \cdot 50) + (E_{T_s}^{18} \cdot \frac{100}{\pi}) \tag{12}$$

Table 3 gives a schematic overview of the parameters used in each scenario, where scenario 0 represents the standard case, tested for all configurations, N1 is the number of drones at the starting point, N2 the number of drones at the turning or end point, C_W the drag coefficient and θ the energy recovery coefficient. In scenario 0, tests are carried out for all configurations with the same number of drones at the start and at the end of the route (N1 = N2).

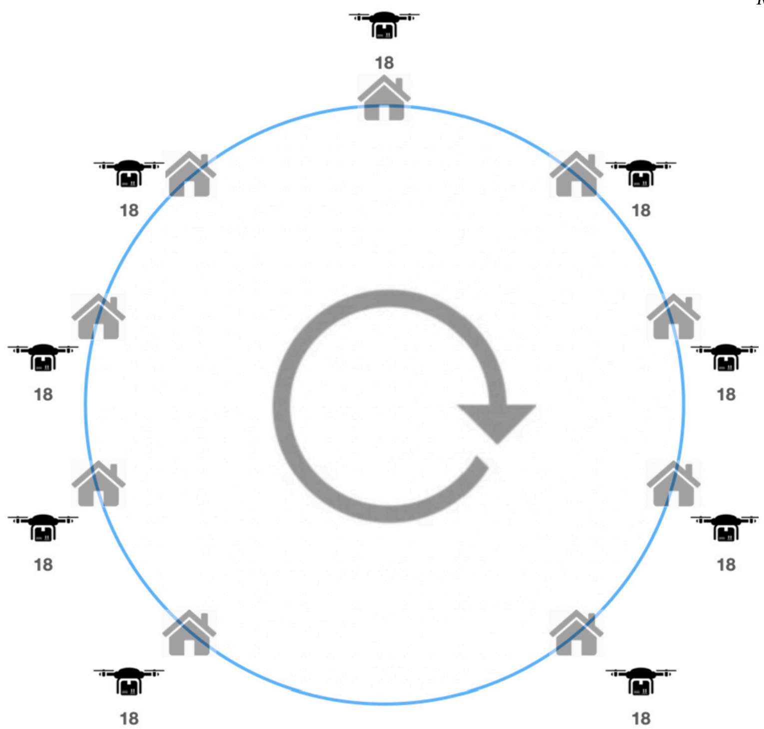

Fig. 9. Scenario 2 - All drones fly the circular route once in one flock starting at the depot and returning to it.

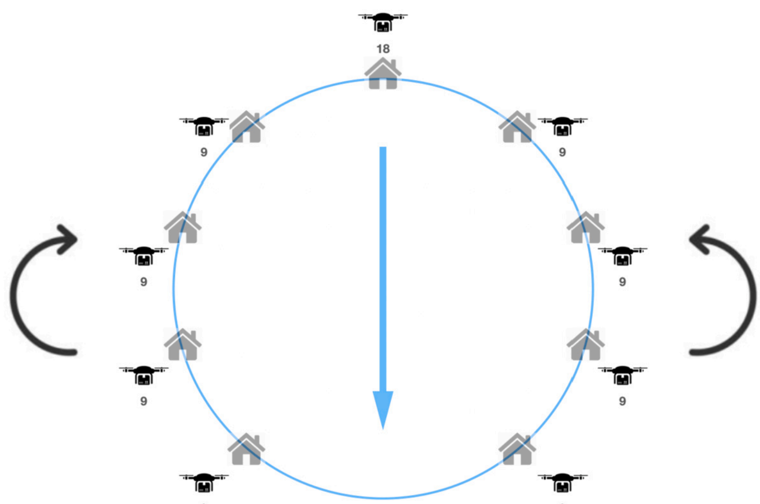

Fig. 10. Scenario 3 - Half of the drones fly in group an equal part of the circular path and the whole flock returns via a straight line.

Table 3
Values of C_W and θ for all scenarios.

Scenario	Configuration	N1	N2	Value C_W	Value θ
Scenario 0	Vertical line	N1 = N2	N1 = N2	1.17	0.8
	V-Shape	N1 = N2	N1 = N2	0.5	0.9
	Diamond	N1 = N2	N1 = N2	0.8	0.6
	Square	N1 = N2	N1 = N2	1.05	0.6
	Horizontal line	N1 = N2	N1 = N2	1.17	0.2
Scenario 1	Vertical line	18	2	1.17	0.8
	V-Shape	18	2	0.5	0.9
Scenario 2	Vertical line	18	18	1.17	0.8
	V-Shape	18	18	0.5	0.9
Scenario 3	Vertical line	9	18	1.17	0.8
	V-Shape	9	18	0.5	0.9

4. Results

4.1. V-Shape solution

4.1.1. Required energy versus angle of attack

Fig. 11 is showing the same configuration as discussed in paragraph 3.1, but with an optimized route with minimal energy consumption. Where Fig. 1 showed randoms routes that can be flown from customer to customer and back to the depot, Fig. 11 shows the routes after optimization, thus with minimal energy required.

Figs. 12 to 16 give a graphic overview of the energy needed for flocks with a different number of drones - varying from 4 (Fig. 12) to 36 (Fig. 16) - versus the angle of attack of the wind involved, ranging from 0° to 180°. Every point depicted is the result of 10 runs of the V-Shape algorithm, of which the lowest value has been taken. Hence, since the V-Shape algorithm is a meta-heuristic, the outcome of each run can dif-

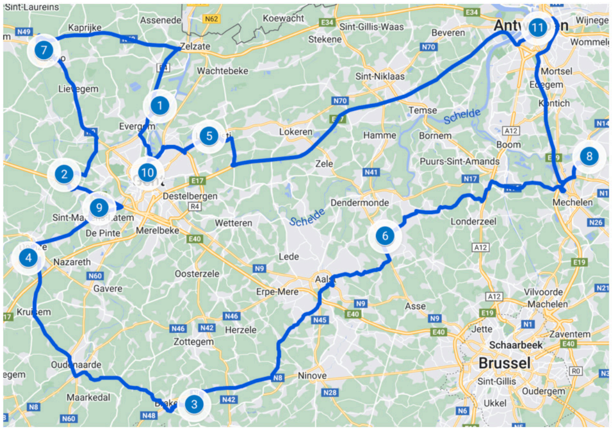

Fig. 11. Optimal route for a flock of drones.

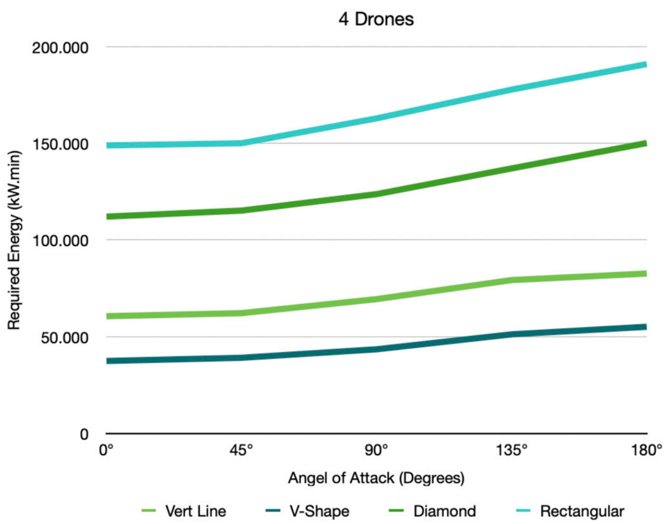

Fig. 12. Power needed by a flock of 4 drones flying the total distance in different configurations for changing angles of attack of the wind.

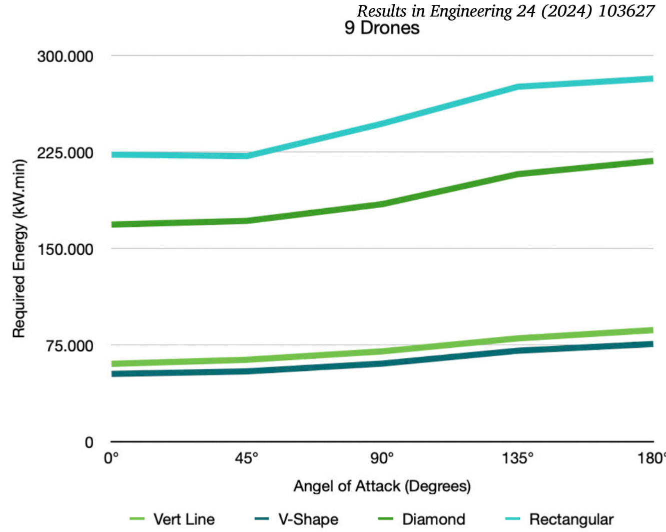

Fig. 13. Power needed by a flock of 9 drones flying the total distance in different configurations for changing angles of attack of the wind.

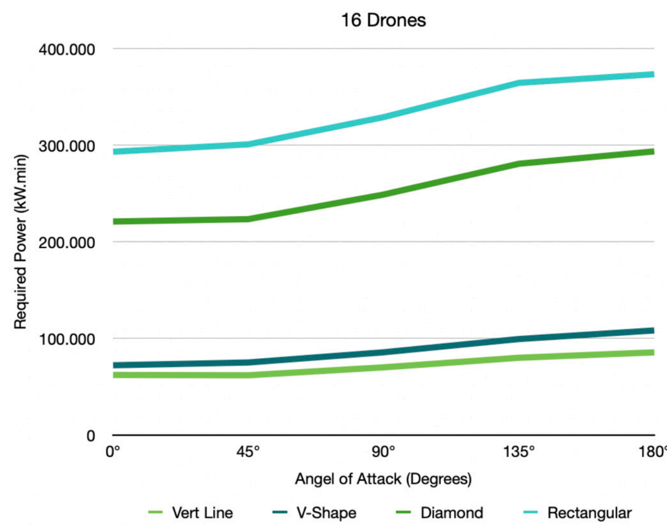

Fig. 14. Power needed by a flock of 16 drones flying the total distance in different configurations for changing angles of attack of the wind.

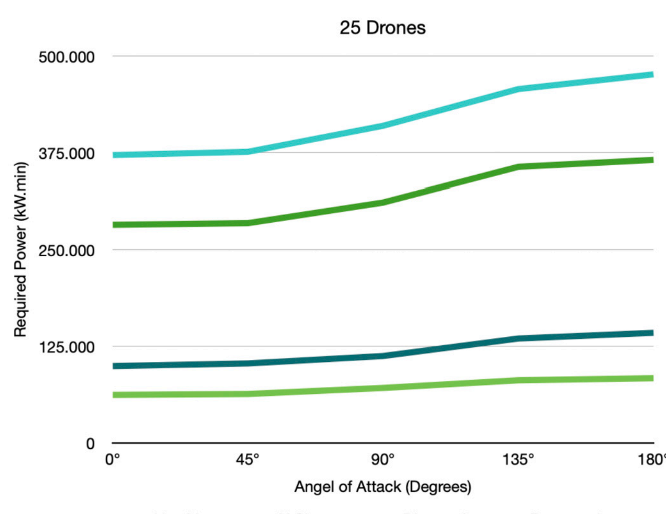

Fig. 15. Power needed by a flock of 25 drones flying the total distance in different configurations for changing angles of attack of the wind.

fer and therefore multiple runs of the algorithm are necessary to find the optimum. All results are calculated taking into account the following parameters: the density of the surrounding air is 1.225 $\frac{kg}{m^3}$, the wind speed is set at 5 $\frac{m}{s}$ and the flock moves at 10 $\frac{m}{s}$. The values for the drag coefficient C_W and the energy recovery coefficient θ for the five studied configurations are listed in Table 3. The algorithm is run with a flock count of 30 and both α and β equal to 1.1. Thereby, α must be larger than 0 and β larger than 1. To equalize the importance of the attractiveness γ_{ij} and the energy ϵ_{ij} on the probability p_{ij}^{f} (Equation (6)), both values for α and β are identical. In this paper, all calculations only take the drag caused by the speed and the shape into account, meaning that all other factors like wake turbulence - a disturbance in the atmosphere that forms behind an object as it passes through the air - are left out of the equation. Furthermore the amount of configurations is limited to five and the number of drones in a configuration tested evolves quadratically to make calculations of the surfaces more straightforward.

The surface exposed to drag of the different configurations is calculated by using the following formula's:

$$A_{Vertical} = A_{Drone} \tag{13}$$

$$A_{Horizontal} = A_{Drone} * (number of drones) \tag{14}$$

$$A_{Square} = A_{Drone} * \sqrt{number of drones} \tag{15}$$

$$A_{Diamond} = A_{Drone} * \sqrt{number of drones} \tag{16}$$

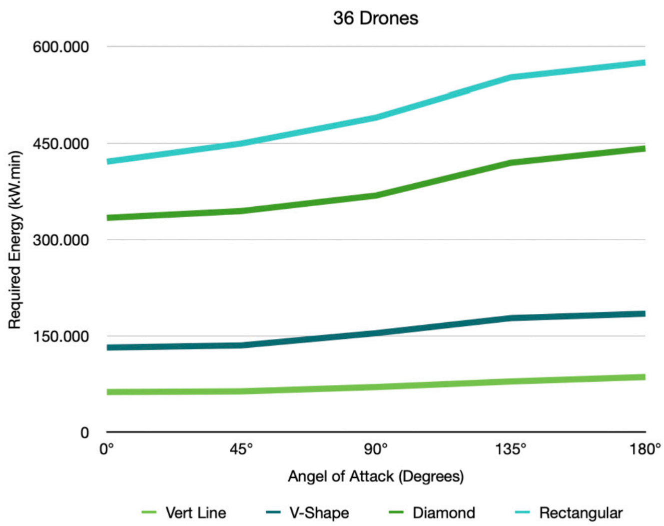

Fig. 16. Power needed by a flock of 36 drones flying the total distance in different configurations for changing angles of attack of the wind.

$$A_{V-Shape} = 1.5 * A_{Drone} + (number of drones - 3) * \frac{A_{drone}}{8} \tag{17}$$

Fig. 17 shows the surfaces opposite to drag for a flock of 9 drones in the different configurations. One drone is considered to have a surface of 0.5 square meters. The presented results are obtained by applying equations (13) to (17). Remark that the surface opposite to drag of the vertical configuration remains constant and the V-Shape shows a smaller value than that of the square and the diamond shape.

The curves in Figs. 12 to 16 show the energy needed (in kW.min) to overcome the drag for each configuration for flocks of 4, 9, 16, 25 and 36 drones and for angle of attacks of 0°, 45°, 90°, 135° and 180°. The results show that for the same amount of drones in a flock, the energy necessary for overcoming the drag rises when the wind turns from 0 degrees (tailwind) to 180 degrees (headwind). For the same angle of attack and for flocks of 4 and 9 drones, the amount of energy required (in kW.min) is the lowest for the V-Shape and the highest for the horizontal line configuration. Hence, the line representing the energy needed by a flock in vertical configuration lies above the line representing the same parameter for a V-shaped flock of drones (Figs. 12 and 13). This implies that the most efficient way to fly a certain route will be in the V-Shape configuration because the lower drag coefficient compensates for the slightly higher surface exposed to drag. In absolute values, the flock of 4 drones in a vertical line requires 1.6 times more energy than the V-Shape, while the diamond shape needs 3 times the energy, the rectangular form 4 times and the horizontal shape 26 times the energy required in the V-Shape, due to the much larger surface exposed to the wind. For a group of 9 drones, the vertical shape only requires 1.15 times the energy the V-Shape needs. For flocks with 16 drones or higher the V-Shape is no longer the most energy efficient way to fly, but the vertical line in which all drones move directly behind each other. This is due to the fact that for the vertical line configuration, the surface exposed to the drag stays the same, but increases for all other configurations and thus at a certain threshold - at 10 drones - this surface surpasses the higher drag coefficient, making the total drag higher. This is shown in Figs. 14 to 16 in which the line for the vertical configuration is situated at the bottom, representing the lowest amount of required energy. The Figs. 12 to 16 do not contain the energy line for the horizontal configuration, since the values calculated for this shape are very high in comparison to those for the other configurations, ranging between 6 to 18 times the amount required for the next best, square shape. The higher the number of drones, the larger the distance between the lines becomes, due to the increasing amount of surface exposed to drag (see equations 22 to 26). Independent of the number of drones in the flock, the vertical line and the V-Shape flocks always require the least energy. However,

Table 4
Energy consumption for a flock of 500 drones for different angles of attack of the wind ψ.

Power needed to travel a distance in kW.min			
Configuration	$\psi = 0°$	$\psi = 90°$	$\psi = 180°$
Vertical line	61.5	70.2	86.7
V-Shape	1520.9	1731.5	2166.1
Diamond	1262.3	1403.8	1649.9
Square	1704.7	1842.4	2165.5

Table 5
Values of ΔG_W for ψ equal to 90° and different number of drones V, varying from 4 to 500.

Configuration	V = 4	V = 9	V = 16	V = 25	V = 36	V = 500
Vertical line	37.3%	15.7%	-22.3%	-36.8%	-119.4%	-2368%
Diamond	64.7%	67.1%	65.6%	63.9%	58.2%	-23.3%
Square	73.2%	75.4%	74.0%	72.6%	68.5%	6.0%
Horizontal line	99.6%	97.4%	97.9%	98.3%	98,3%	98.7%

when expanding the flock of drones to 500 units, further conclusions can be drawn. Table 4 shows the amount of energy needed by a large flock when moving in different configurations and this for headwind, tailwind, and pure crosswind. Based on these results, it can be deduced that the vertical line still remains the best by far - almost 2400% better than the V-Shape - but the diamond configuration now becomes 20% to 30% more energy efficient than the V-Shape, depending on the direction of the wind. Tests have further shown that the cut-over amount of drones in a flock at which the diamond configuration becomes more energy efficient than the V-Shape, is around 310. Finally, the difference in energy consumption between the V-Shape and the rectangular configuration is reduced, to 11%, 6% and 0%, depending on the wind direction.

Based on the absolute energy values, ΔG_W is calculated for all configurations and for different number of drones in the flock, for an angle of attack of 90 degrees. As indicated before, the vertical line configuration demands more energy than the amount required for the reference V-Shape when the amount of drones is limited to 9. When the configuration exists of 16 drones or more, the value for the vertical line becomes negative, meaning that the amount of energy necessary is less than for the reference configuration. The other deviation percentages stay more or less the same for all other configurations and show that the V-Shape remains better than the diamond one, the diamond configuration better than the square one, and all of them better than the horizontal line. However, when expanding to very large flocks of drones, the diamond shape becomes also 23.3% more energy efficient than the V-Shape, on top of the vertical line. All these data are summarized in Table 5.

4.1.2. *Relative travel time versus number of drones*

Fig. 18 shows the relative travel time for each configuration in relation to the number of drones in the flock. For example, for ψ values equal to 90° and a configuration of 9 drones, the flock in V-Shape traveled 547 minutes, while the flock in the vertical line configuration has flown 578 minutes to reach the same goal. For a flock of 25 drones, the flock in vertical line configuration has only traveled 306 minutes instead of 536 minutes for the drones flying in V-Shape. The results also show that the V-Shape is again the best for smaller flocks of 4 and 9 drones. In the 4 drones case, the vertical line has a relative travel time 1.4 times that of the V-Shape, the diamond shape doubles the travel time, the rectangular 2.64, and the horizontal line 5.9 times the V-shape travel time. When looking at the flock with 9 drones, the respective values are 1.05, 2.1, 2.8, and finally 9.4 times the travel time of the V-Shape. As the flock reaches 10 drones, the relative travel time line of the vertical line configuration crosses the V-shape line, meaning that for larger flocks, the vertical line becomes the shortest relative to the V-shape and all other shapes. In the configuration with 36 drones, the

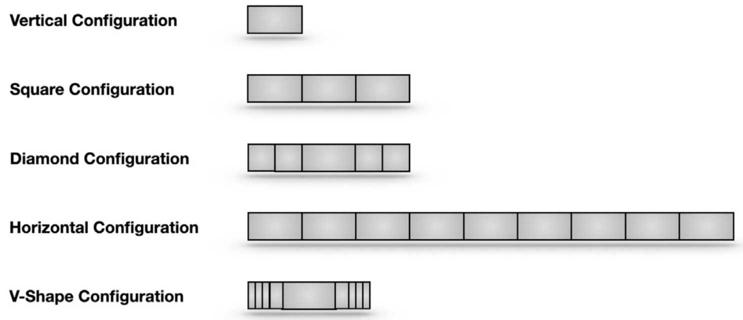

Fig. 17. Surface opposite to drag for 9 Drones in all configurations.

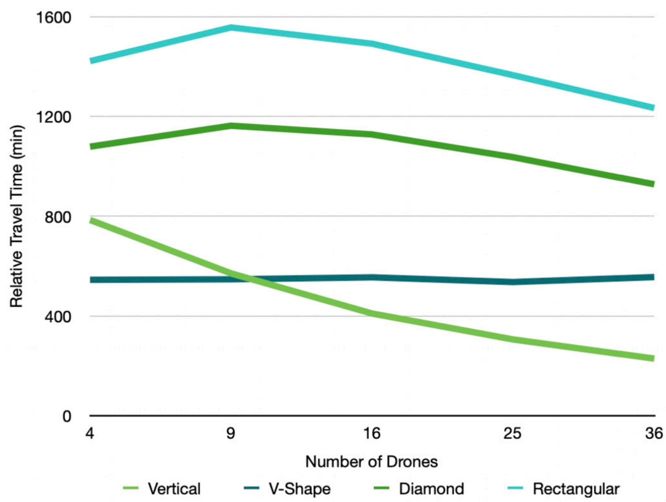

Fig. 18. Relative Travel Time vs Number of Drones.

Table 6
Values of ΔG_D for all shapes and different numbers of drones.

Configuration	4 drones	9 drones	16 drones	25 drones	36 drones
Vertical line	30.6%	4.2%	-35.4%	-75.2%	-142.8%
Diamond	49.5%	53.0%	50.8%	48.3%	40.1%
Square	61.7%	64.9%	62.8%	60.8%	54.9%
Horizontal line	83.6%	89.6%	91.4%	93.0%	93.3%

vertical line configuration needs 0.55 times the travel time the V-shape needs to cover (min), while the diamond shape still travels 1.9 times the reference travel time, the rectangular constellation 2.5 times and the horizontal line 14.2 times. Finally, for a flock of 500 drones, the vertical line configuration is 27.5 times faster than the V-Shape and the diamond configuration 1.77 times better than the V-Shape. The number of drones in a flock at which the diamond shape becomes faster than the V-Shape is around 155. Opposite to the conclusions for the energy evolution, the values of the relative travel time (Fig. 18) are independent of the angle of attack of the wind. Hence, the relative travel time calculation shown in equation (1) does not contain the angle of attack, nor the wind speed. Since the V-Shape is the reference one, the optimal travel time calculated for this configuration is the real minimal distance to be covered, while all other travel times are in reference to this V-Shape.

Based on the relative travel time values, ΔG_D is calculated for all configurations and for several amounts of drones in the flock. Again the same conclusions can be drawn as before, namely that for flocks of 4 and 9 drones the V-Shape is the optimal configuration and from 16 drones on, the vertical line is better to move in. See Table 6.

The average price of 1 kWh in Belgium in November 2024 is 0.3€ [18]. For a flock of 36 drones flying a distance of plus-minus 550 kilometers or minutes (1 km equals 1 minute) with a 90 degrees side wind,

Table 7
Energy consumption per duo of drones in scenario 2.

Power needed to travel a distance in W.min			
Location	V-Shape	Vertical Line	V-Shape Single
Customer 1	183.20	140.72	122.58
Customer 2	194.34	158.31	132.15
Customer 3	202.86	180.92	149.31
Customer 4	209.81	211.08	161.35
Customer 5	229.50	253.29	170.67
Customer 6	262.87	316.61	200.65
Customer 7	305.33	422.15	261.30
Customer 8	396.94	633.23	354.35
Customer 9	679.13	1266.45	637.55

the price of the total energy required by every configuration is obtained by dividing the calculated energy value by 60 - to convert to kWh - and then multiplying it by 0.3€. This resulted in the following cost of energy for the whole flock: 352€ for the vertical configuration, 771€ for the V-Shape, 1843€ for the diamond and 2450€ for the rectangular shape. It is thus the most cost efficient to fly with all drones in a vertical line and almost double as expensive to fly in a V-Shape.

4.2. Use cases - flocks of 18 drones

Table 7 lists the amount of energy consumed by a duo of drones as they travel according to scenario one, where at each customer two drones remain at the visited location. For scenario 1, this value is calculated as the sum of all amounts listed in Table 7, and finally multiplied by two for the round trip (Equation (9)). The total amount corresponding to scenario 2 is become by multiplying the total energy needed for the whole flock, by the total distance to be traveled, being 100 kilometers (Equation (10)). Finally the data for scenario 3 are computed by multiplying the amount of energy needed by a flock of 9 drones - determined by executing the V-Shape algorithm - by the half of the total distance to be traveled (50 kilometers) plus the energy of the 18 drones over the center line distance (Equation (11) and (12)).

All calculations are done for a flock traveling at 10 meters per second with a side wind of 5 meters per second and an angle of attack of 90 degrees. The last column in Table 7 finally shows the energy values for scenario 1, but then flying in a V-shape with 9 drones, one drone staying behind at each customer. The numbers prove that flying with single drones instead of duo's does not imply that the energy needed is doubled.

Table 8 shows that when choosing to fly in a V-Shape, the drones use the least average energy when moving as described in scenario 1 and thus leaving two drones at each customer. It is then, again according to the results, better to fly in a V-Shape than in a vertical line. Furthermore, we can conclude that when flying in a V-Shape in two groups of 9 drones at each side of the circle and returning as a flock of 18 drones in a vertical line (scenario 3), less energy is consumed than when flying the whole route in a flock of 18 drones. The opposite is true for the same scenario

Table 8
Total energy consumption for all drones in all scenarios.

Total Power needed per drone to travel a distance in W.min				
Configuration	Scenario 1	Scenario 2	Scenario 3	Two by Two
V-Shape	296.00	916.01	836.86	1516.43
Vertical Line	398.08	703.59	927.54	2827.88

but with two flocks of 9 drones flying in a vertical line. The last column in Table 8 finally shows the total energy needed when each customer is visited by two drones that always depart from and return to the same location. This appears to be the most energy consuming scenario.

5. Conclusions

The results obtained by solving an ACO based algorithm - named V-Shape algorithm by the author - show that the lowest amount of energy is required when flying in V-Shape for a flock of 4 and 9 drones, but for flocks of 16, 25 and 36 drones, the vertical line configuration is the most efficient way to travel. The direction of the wind plays a role in the calculation of the necessary energy, resulting in a decrease of the amount required when wind is coming from behind the flock. The V-Shape is considered the reference flock configuration and relative travel times and amounts of necessary energy are calculated in relation to this arrangement. For 4 drones the vertical line configuration appears to demand 37.3% more energy than the V-shape, while the diamond form requires 64.7% more energy. However, a vertical flock of 25 drones consumes 36.8% less energy than then V-Shape, but the V-Shape is still 63.9% more energy efficient than the diamond configuration. Overall we can conclude that depending on the number of drones in the flock, the vertical configuration or the V-Shape configuration appears to be the most energy efficient, except for very large flocks of drones (500 units) in which the diamond also becomes - on top of the vertical line - a better configuration (23.3%) to fly in than the V-Shape.

In a second phase, the V-Shape algorithm was applied to three different scenario's for a group of 18 drones traveling via 9 customers each at 10 kilometers from each other and arranged in a circle. For the V-shape, scenario 1 - drones are left behind two by two for drop off and picked up again by the flock flying back via a circular path - is 67.7% better than scenario 2, where the whole flock flies the circular route once. It is thereby also 64.6% more energy efficient than scenario 3, in which half of the drones fly half of the circular path and the whole flock return via a straight line. For the vertical line configuration, scenario 1 is 43.4% more efficient than scenario 2, and 57.1% better than scenario 3. Furthermore, the V-Shape is the best configuration in scenario 1 and 3, but the worst in scenario 2, where the vertical line is better. Finally, all scenarios appear to be much better than the model in which all drones depart two by two from the depot and return to this depot afterwards via a straight line. Overall we can conclude that for large groups of drones, it is better to travel in a vertical line, while for smaller flocks of drones, the V-Shape is the most energy efficient, when only the drag is taken into account as a determining factor.

6. Discussion

In future research, our paper can be used as a basis for determining flock behavior and configurations when using groups of drones to deliver packages, small or large, or in other domains of application, like military or transport aviation, or in agriculture for large surface spraying. Also, other parameters can be taken into account when determining the optimal configurations in which drones must fly to consume the least amount of energy. Hence, in this paper, the influence of, for example, the wake turbulence on the lift of the drones in the formation as well as the turbulence behind the whole flock are considered in a simplified form, being the energy recovery coefficient. Previous research has shown that these can be of influence in choosing the best shape to fly in. Furthermore, other configurations can be studied apart from the five that were discussed in this paper, since the model is expandable to every value of the drag coefficient and the simplified energy recovery parameter. In short, all applications that need flocks of drones, can use our research to determine via which track and in which shape the drones must fly to be as energy efficient as possible.

CRediT authorship contribution statement

E. De Kuyffer: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization. **W. Joseph:** Writing – review & editing, Supervision. **L. Martens:** Supervision. **T. De Pessemier:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Erik De Kuyffer reports administrative support and writing assistance were provided by imec-WAVES-UGent. Erik De Kuyffer reports a relationship with imec-WAVES-UGent that includes: non-financial support and travel reimbursement. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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