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MODELING INTERNAL LOGISTICS BY USING DRONES ON THE STAGE OF ASSEMBLY OF PRODUCTS

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Abstract

The subject addressed in this paper is the issue of using an UAV type Quadcopter in the internal logistics within a manufacturing plant, particularly at the stage of assembly and /or customization of products. The vertical takeoff and landing, as well as horizontal flight, both with the characteristic of low speed and high precision, are major requirements for this work. The quadrotor architecture has been chosen for analysis because of its low dimensions, good maneuverability, simple mechanics and available payload capacity. As a major drawback, the high energy consumption when operating is a constraint to be modeled and optimized. In the first step, an internal logistics modeling is performed in order to determine the location of depots, clusters and sub-clusters; workstations are defined and routes are generated using a genetic algorithm for each quadcopter of a particular fleet. In a second step, the weight to be transported by each quadcopter is determined, depending on the assigned route and workstations that should go through the sequence either to remove materials (picking) or to deliver materials (delivery). In a third step, it is determined the electric power amount to be drained off the battery of every quadcopter for a given route depending on the weight carried, distance covered, number of workstations visited and the quadcopter aerodynamic efficiency.

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Keywords: Genetic Algorithm, Quadcopter, Traveling Salesman Problem, Energy Saving of Battery

1. Introduction

In recent years, in the world of robotics, a growing interest has been evidenced in UAV (Unmanned Aerial Vehicle). Various structures and configurations have been developed to enable 3D movements. Each of them have advantages and disadvantages. The vertical takeoff and landing, as well as horizontal flight avoiding obstacles, both with characteristics of low speed and high precision, are fundamental requirements in the subject. However, platforms that show these features with four, six and eight rotors have the ability only for vertical and horizontal flight, and low speed movement. The quadrotor architecture has been chosen for

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analysis because of its low dimensions, good maneuverability, simple mechanics and good relationship between total weight and payload capacity. All these factors are also limited by the high consumption of energy required for operation.

Some classical heuristics for vehicle routing problem (VRP) are based on the principle of first grouping and then routing, such as Sweep Algorithms. The first phase is to generate groups (sub-clusters) of machines; each group of machines would be on a same drone route in the final solution. Then, as a second step, a route for the drone is created for each sub-cluster which must visit all of the machines in the sub-cluster. Therefore, constructing routes for each sub-cluster is converted into a TSP (Traveling Salesman Problem), which can be solved in an exact or approximate form depending on the number of machines in it.

2. Description of a generalized custom-made assembly process

In many manufacturing plants making products such as footwear, toys, plastics-made objects for home and industrial use, there is a major problem in the internal logistics of these assembly or customizing facilities [1, 5] due to high number of products, machines, and routings. In order to study this situation, a manufacturer of injection molding plastic products is used as reference model; final products are two types: storage boxes and trays for home, retail and industrial applications, which are assembled from parts picked up at warehouses and delivered at assembly lines in the plant. Fig 1.(a) shows a materials supply scheme from two warehouses adjacent to the assembly plant towards a workstation (WS) or mini-assembly line. This material supply instance may be repeated for the dozens of workstations (WSs) or mini-assembly lines existing in plants of this type. In this work, a proposal for transportation of materials and semi-finished products by using a quadcopter fleet is shown.

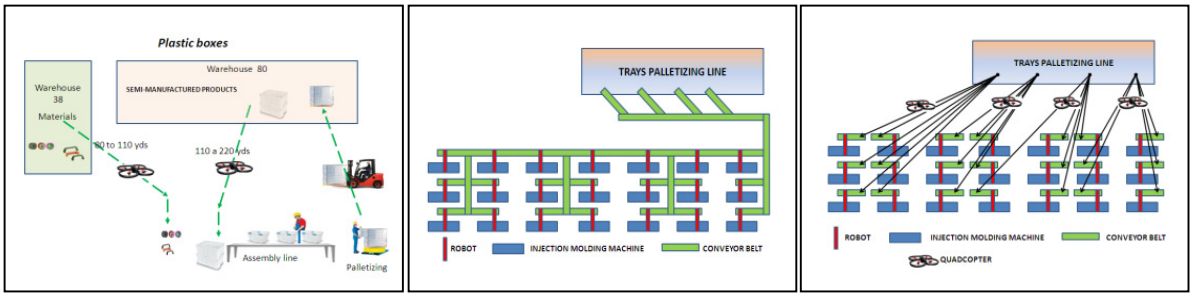

Fig. 1.(a) Delivery of materials to WSs (b) Current situation (c) Proposal

An analogous situation occurs in the manufacturing of plastic products, which corresponds to the pickup of parts produced at injection molding machines to be carried to the palletizing line. Fig 1.(b) shows (in green color) the current transport system of products via conveyor belts from injection molding machines to the palletizing line.

In Fig 1.(c), it is proposed a replacement of the conveyor belts by a fleet of quadcopters for product pickup from injection molding machines to the palletizing line.

3. Characterization of the problem

The situation described above for both the delivery and the pickup, can be characterized and defined in generic terms as corresponding to a workshop with dozens of machines, which are supplied with materials from a depot. Fig 2.(a) shows a layout in which the positions of the WSs in the plane (X,Y) are shown as a blue dot, which are supplied with materials from a depot represented by the yellow triangle. As already described above, the

first step is to generate clusters or groupings of dots considering constraints such as; total payload capacity of the quadcopter, time, energy level of the batteries, etc. Each of these clusters will contain, as a starting point, a depot, from where the quadcopter starts and ends the circuit, after performing the pickup or delivery of products.

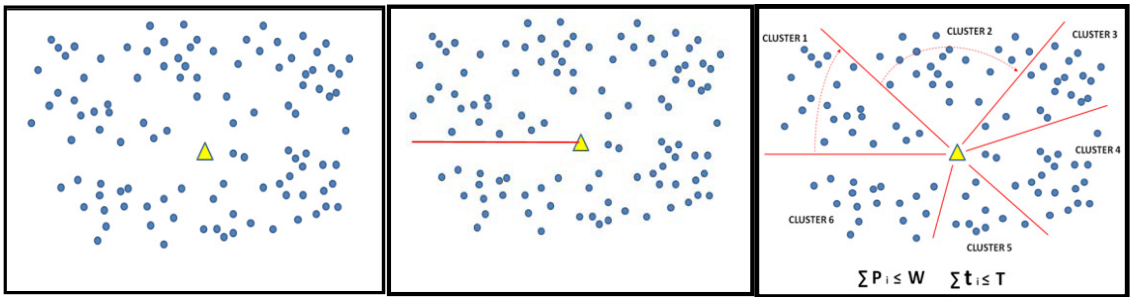

Fig. 2. (a) positions of WS y DC (b) ray (c) Formation of clusters

4. Methodology

4.1. Generation of clusters

For the first phase, i.e. to form clusters, the method used is the *sweep algorithm*. In this heuristic [6-7], clusters are formed by turning a ray clockwise with origin in the warehouse, see Fig 2.(b), and incorporating the machines "swept" by that ray until a constraint is exceeded, e.g. the total payload capacity of the assigned quadcopter, the remaining power of its battery or other constraint. For the example shown in Fig 2.(a), six clusters are obtained as shown in Fig 2.(c). If one of these clusters is taken, e.g. cluster 1, as shown in Fig 3.(a), and the vehicle is then routed by solving a TSP either exactly or approximately, the route of the quadcopter assigned to that cluster is obtained, as shown in Fig 3.(b)

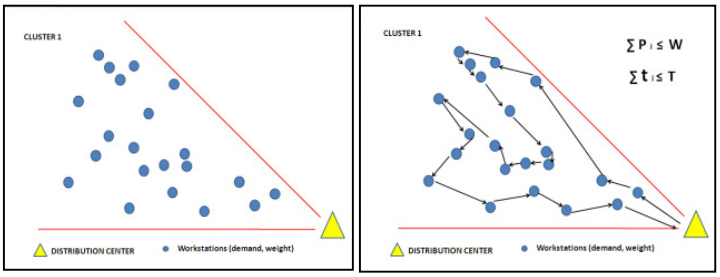

Fig. 3 (a) Cluster1 (b) TSP of Cluster1

It is assumed that the position of each workstation is given by its polar coordinates in a system having the depot as origin. Summarizing, the steps of the algorithm are as follows:

Step 1 (initialization)

- Choose an unoccupied quadcopter k. This should be selected from a subset of unoccupied quadcopters according to a method of choice, where a set of variables are weighted up, mainly the remaining battery charge.

Step 2 (selection)

- Sort the WSs according to the inclination angle (Θ) in relation to a reference point, in this case the depot, in increasing form.

- If two WSs have an inclination angle of equal value (Θ, r), first place the one with lower r value.
- Assign the workstation to the cluster until the completion of the quadcopter payload capacity, or as other constraint emerges, such as low battery. If all the WSs already belong to a cluster, and no more WSs can be added to the cluster due to constraints, go to step3.

Step 3 (optimization)

- Optimize the route using an algorithm that solves the TSP, in this case a GA, for the sub-cluster generated, considering or not the weight of the supplies to be delivered at each workstation. GA parameters should be adjusted according to the number of WSs in the sub-cluster.

4.2. Generation of routes using Genetic Algorithm (GA) for each cluster

Here, the necessary steps for creating the code and run the GA to solve the TSP of each Cluster are listed below.
Step 1.- Generate the matrix of workstation positions belonging to the cluster within a polygon, where the position of the depot is placed at the origin. The WSs in the cluster are all those that a drone has to visit to deliver or pick up materials in only one trip. This matrix is called ***locations***, and is a matrix of (n, 2), where ***n*** is the number of WSs of the cluster. The ***locations*** matrix is formed by the coordinates X, Y of the WSs belonging to the same cluster, given by the sweep algorithm method. The position of each WS is obtained from the plant layout. As an example, the positions of 10 WSs and depot are defined in Matlab as follows:

locations = [0 0; 16 30; 40 30; 17 70; 70 60; 40 10; 30 20; 10 60; 16 70; 10 70; 0 40]

The first position (X=0, Y=0) of the matrix ***locations*** belongs to the depot, the rest of positions (X, Y) of the matrix correspond to the 10 WSs.

Step 2.- Generation of the distance matrix between the points on the cluster, called ***distances***.
Step 3.-Generation of the shortest route using GA, finding a possible solution to the TSP in every cluster.
The input for this step is the generated matrix ***distances***. First, a structure of options is created to indicate a custom data type, such as population size, number of generations, etc. Secondly, Matlab functions are used for the creation of the population, selection, cross and mutation.

5. Results of the model using GA

In order to determine the performance of the GA [8-9] that generates the quadcopter path, production scenarios were tested with different numbers of WSs to be supplied with the materials from a depot. It is assumed that the weight of these materials is similar or very light. In this case, to assign a path to the quadcopter to perform the delivery of materials, the weight of these materials is not considered as a variable of decision, only considering the distance between the WSs. Weight is considered at a later stage in order to calculate energy consumption on a particular route. Table 1 shows the results of the TSP using GA with 200 generations, for different numbers of WSs. Ten runs for each layout from 10 to 50 WSs are shown. It can be seen that for a layout up to 10 WSs, the GA immediately generates optimal routes in very suitable times. Therefore, for clusters with 10 or fewer WSs, it can be expected to obtain the optimal route selecting the lowest value obtained with a few runs of the GA. Table 1 also shows that for 10 WSs, all GA runs provided the same fitness as a result. Therefore, there is no difference between the mean and the best fitness, as shown in Table 2. The accuracy of the GA still remains good between 10 and 15 WSs. For instance, it can be observed that for 15 WSs, only one in 10 runs, the algorithm did not provide the optimal result. Between 15 and 20 WSs the lowest fitness is repeated with a certain frequency and with a few runs a good result can be obtained in order to provide the quadcopter with an appropriate route.

Table 1. Results of total distance (mt) for 10 runs of the GA with 200 generations.

	N° Run of the GA									
N°of WS	1	2	3	4	5	6	7	8	9	10
10	247.47	247.47	247.47	247.47	247.47	247.47	247.47	247.47	247.47	247.47
15	273.90	287.96	273.90	273.90	273.90	273.90	273.90	273.90	273.90	273.90
20	315.96	316.95	316.95	315.96	344.18	315.96	315.96	342.99	315.96	342.99
30	423.63	405.70	408.48	421.58	413.00	422.89	401.86	420.94	445.68	430.37
40	527.20	494.46	502.80	464.94	524.75	477.29	557.75	500.64	509.29	508.31
50	583.60	539.44	589.29	616.02	615.17	631.17	629.58	629.85	638.73	595.56

Table 2 shows the mean of the results of ten runs of the GA for each group of WSs and its standard deviation (STD) and Relative Standard Deviation (RSD)

Table 2. Summary of results of the GA

N°of WS	Best path length	Mean	STD	RSD %
10	247.47	247.47	0	0
15	273.90	275.30	4.45	1.62
20	315.96	324.39	13.12	4.04
30	401.86	419.41	12.93	3.08
40	464.94	506.74	26.19	5.17
50	539.44	606.84	30.42	5.01

Fig 4.(a) shows that the higher the number of WSs in the cluster is, the higher the difference between the mean and best fitness, i.e. there is an increase in the dispersion in the results of GA with 200 generations.

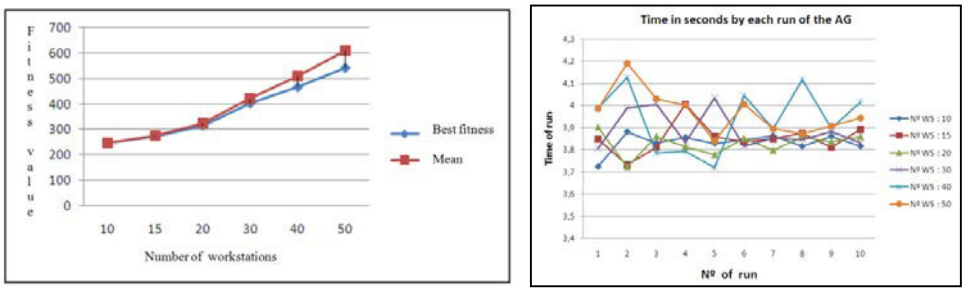

Fig.4.(a) Difference between mean and best fitness (b) Running time of the GA

Regarding the time taken by the GA [8-9] to provide an outcome, CPU-time of the GA is shown in Table 3 for ten GA runs for each of the clusters of WS (10 to 50).

Table 3. CPU-Time taken by the GA in 10 runs with 200 generations. (sec)

	N° run of the GA									
N° of WSs	1	2	3	4	5	6	7	8	9	10
10	3.72	3.88	3.83	3.86	3.83	3.85	3.86	3.82	3.86	3.82
15	3.85	3.73	3.81	4.01	3.86	3.84	3.85	3.87	3.81	3.89
20	3.90	3.72	3.86	3.81	3.78	3.85	3.80	3.86	3.84	3.86
30	3.81	3.99	4.01	421.58	4.03	3.82	3.85	3.85	3.88	3.83
40	3.99	4.13	3.79	464.94	3.72	4.05	3.89	4.12	3.90	4.02
50	3.99	4.19	4.00	616.02	3.84	4.01	3.89	3.87	3.91	3.94

Based on the data in Table 3, the mean and standard deviation are obtained, as shown in Table 4. It is evidenced that both the mean and the STD of time in the 10 runs of the GA for each one of the groups of WS (10 to 50) have no difference. This is because in genetic algorithms, a run-time is proportional to the number of

generations defined, which in this case is fixed at 200 generations for all cases. However, small increases can be seen in the mean time as the number of WSs considered in the run increases. This is also reflected in Fig 4.(b) where it is observed each time in each of the GA runs by cluster of WS.

Table 4. Mean and STD of 10 runs of the GA with 200 generations (sec)

N° of WSs	Mean	STD
10	3.83	0.04
15	3.85	0.07
20	3.83	0.05
30	3.89	0.09
40	3.94	0.14
50	3.97	0.10

According to the results shown in Table 1, it is recommended that for a cluster having 30 or more WSs, the number of generations and / or population in the GA code must be increased. However it will result in an increase in the CPU-time of the GA. According to the requirements made for the design of the system in managing a quadcopter fleet, in order to assign materials loads to each quadcopter, optimizing the use of energy and battery duration is imperative. Given the dynamics of the system, the whole process of: creating clusters, selecting a quadcopter, generating its route and assigning the delivery, must occur in the shortest time possible, not exceeding a couple of minutes. It is important therefore that the GA provides an adequate response in the shortest time possible. Next, in Table 5, results of GA runs are shown for 50 WSs and the number of generations varies. The purpose is to determine the impact on time (in seconds) in which the GA provides the result by varying the number of generations in the model.

Table 5. Result of the GA for 50 WSs varying the number the generations

		Path length of GA (mt)			CPU-TIME GA (sec)	
N° of Generations	N° of WS	BEST	MEAN	STD	MEAN	STD
300	50	530.6143	555.8617	13.0781	5.6279	0.047
400	50	501.5421	535.3700	20.6006	7.3773	0.073
490	50	486.8844	517.6826	20.2412	8.9190	0.065
600	50	479.3115	505.0828	13.1281	10.8182	0.089
800	50	467.8809	495.2497	17.6451	15.6451	0.826

In Fig 5.(a), it is observed that, as the number of generations increase, the best values found by the GA decrease. Inversely, Fig 5.(b) shows that CPU-time in GA grows as the number of generations increases.

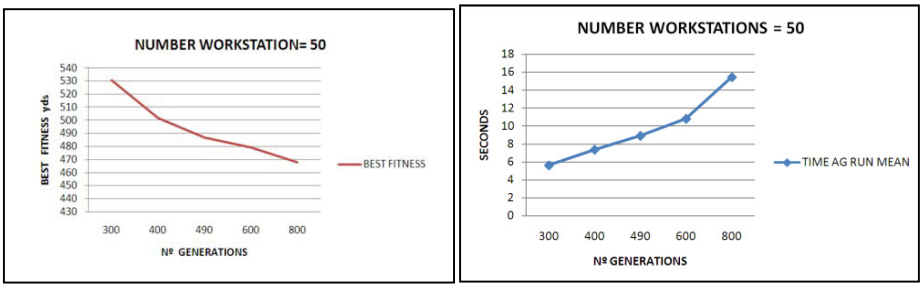

Fig.5.(a) Fitness versus generations b) Mean time versus generations

6. Special cases of applications of GA

There is a variety of cases in which the GA [8-9] must be adapted in order to find an appropriate path for the quadcopter, in many of these cases adapting the matrix of distances is sufficient to find the solution. For example Fig 6.(a) shows a warehouse layout where a quadcopter must travel and collect material from various

positions, go through a corridor towards the WSs area; it continues to visit different points where materials are delivered and finally returns by another corridor and finish in the Depot, the starting point. Fig 6.(a) shows the directions that the GA should respect. In Fig 6.(b) the points which are critical as constraints, are shown in red points. Fig 6.(c) shows the results yielded by the GA. Fig 7 shows the structure of the matrix with sub-matrices, showing the constraints and distances bounded to certain zones.

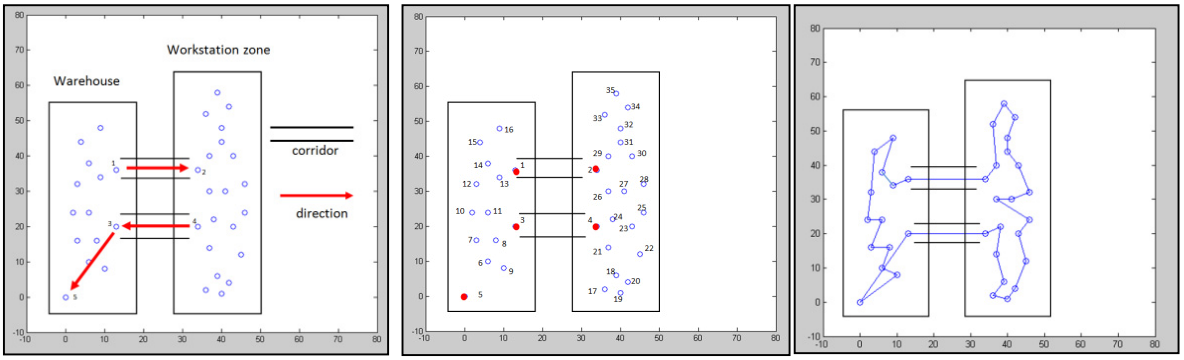

Fig. 6. (a) Compulsory directions (b) Critical points (c) Result of the GA

7. Capacitated VRP (CVRP)

CVRP is an extension of the classical TSP [10-14] discussed above, where every workstation has an associated demand for supplies and quadcopters have a limited payload capacity W. In this case, it is assumed that there is a very big difference in the weight of some supplies transported to certain WSs in contrast with the weight transported to other WSs. Therefore, it should be incorporated as an additional variable in the GA, so that a path is generated for the quadcopters. The GA is expected to prioritize certain WSs that require supplies of a much higher weight than the weight transported to other WSs. With this, the GA solution departs from the Hamiltonian path that can be seen in the TSP shown in the previous cases. Basically, here it is incorporated a weight-matrix into the GA, which is weighted with the distance-matrix in order to generate a weight/distance matrix in the stretches between WSs in which the GA will seek the sequence whose sum of factors is the one with the lowest value. In Fig 8, it is shown the path obtained by the GA for 9 WSs and a depot located in (X = 0, Y = 0) when weights to be moved to the WS are varied.

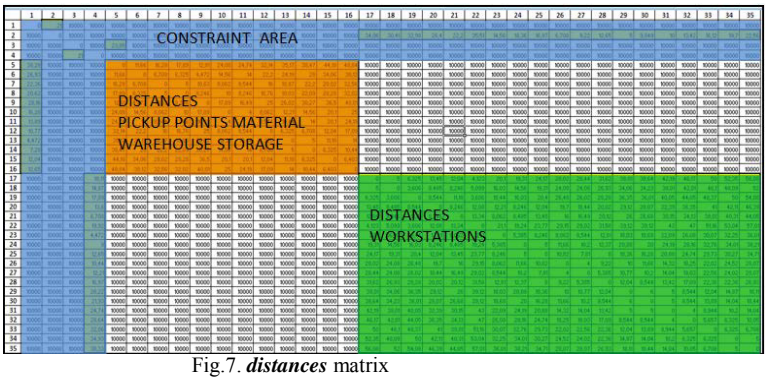

Fig.7. ***distances*** matrix

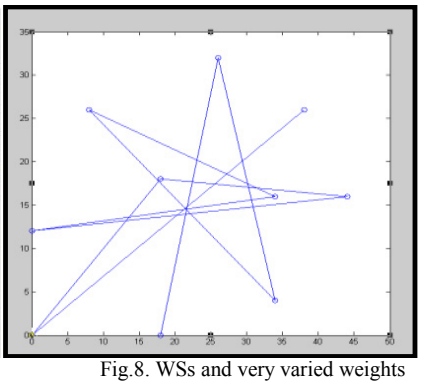

Fig.8. WSs and very varied weights

The results provided by the GA are equivalent; the route is used in the same way than in previous cases. However, the value of the fitness provided in this case, is distorted by the pondered distances. Transported

weight must therefore be calculated for the route suggested by the GA. This is shown in the next section.

8. Calculating the weight carried through the route suggested by the GA

It is imperative to determine the distance traveled and the weight transported by quadcopter, according to the route determined by the VPR (TSP) or the CVPR. This will be the basis, in order to be able to make the calculation of the energy drained from the battery (or batteries) of the quadcopter [15-16]. If the quadcopter follows the route provided by the GA, it is possible to determine the variations in weights transported when delivering the materials in each WS of the path and accumulated travel distances, as shown in Fig 9 for the case in which the quadcopter makes a delivery and Fig 10 for the case in which the quadcopter makes a pickup.

Fig. 9 Transported wight in delivery

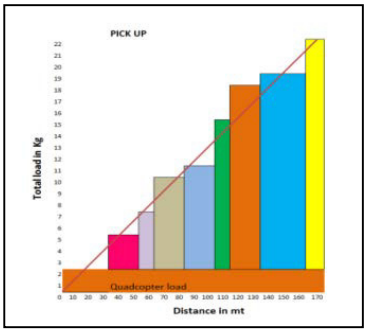

Fig. 10 Transported wight in pickup

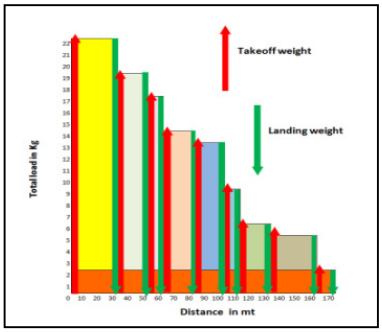

Fig. 11 Dron weight when taking off and landing

One remarkable aspect in both cases, delivery and pick up, is the average value indicated by the line in red, representing, with no major difference and in a simple way to get, the weight carried by the quadcopter depending on the distance. The simplicity of the average value, as shown in Fig 9 and Fig 10, is relevant to achieve the objective of the method, that is, to determine the energy consumed by the quadcopter when performing certain tasks. This average value is valid for most cases of combinations of routes, where weights and distances are similar. However, in situations where there are few WSs and weights of materials very uneven, this average value may not represent the situation and be far from reality. For these cases, weight carried by the quadcopter depending on the distance can be modeled using a treatment with matrices, taking as input the GA path matrix and the so-called matrix of distances among WSs also provided by the GA. In addition, it must be incorporated the weight of quadcopter (structure, battery(ies), electronic devices, engines, etc.) and the energy expended by the number of times that the quadcopter takes off and lands. Then the treatment with matrices to obtain the value of Total Freight (TF) is presented.

$$\boldsymbol{TF = LoadMean + LoadQuad}$$
$$\boldsymbol{LoadMean} = \text{trace}[\text{diag}[[\boldsymbol{distances} .* \boldsymbol{SECSPT}]*[\boldsymbol{\Sigma Pi} - [\boldsymbol{weightACUM}]]^{T}]] \quad (1)$$
$$\boldsymbol{LoadQuad = WQ * \sum_{1}^{n} D_i}$$

Where,
TF : Total freight
LoadMean : Mean of the load
LoadQuad : Load of the quadcopter itself
distances : ***distances*** matrix among WSs provided by the GA
SECSPT : A matrix containing “zeros” and “ones” , where “ones” correspond to the sequence of the GA, the rest of the values of the files and columns must be zero.
Pi : weight of the load assigned to the WSi
weightACUM = [0, P_i, $P_i + P_{i+1}$, ...] : matrix of accumulated weights

WQ: Quadcopter weight

Then, the energy spent in the number of times that the quadcopter will take off and land in a specific route with different weights in each WS, must be added to the energy consumption used by the quadcopter and its payload when transporting. Each of these maneuvers consumes a significant amount of energy given by the following equation.

$$\boldsymbol{TakeoffAndLanding}: \quad \boldsymbol{TakeoffAndLanding} = \left(\sum_1^n \mathbf{P_i} + \mathbf{WQ}\right) * (\boldsymbol{NWS}+1) \tag{2}$$

where
NWS: Number of Workstations

In Fig 11 the quadcopter weight plus some variations in the weight per takeoff and landing are shown. It is also shown the number of times the quadcopter takes off and lands in the process of delivering materials, starting from the Depot, covering WSs and landing back on the depot.

9. Amount of electrical energy required for the route

By using equations of statics and dynamics and data on performance of propellers and motors [16] commercially available, it can be determined the required thrust and calculate energy consumption. Fig 12 shows the power consumption in Watts of a quadcopter of 25kg (5kg own weight and 20 kg payload) for different distances in meters. In blue, it is shown the quadcopter carrying the entire weight from the DC to WS and returning empty to DC. In red, it is shown the pickup or delivery, starting from the DC, delivering or collecting material on each WS on the route provided by the GA and returning the DC. It can be seen in the figure that the power consumption for pickup or delivery is lower since the average weight carried is lighter.

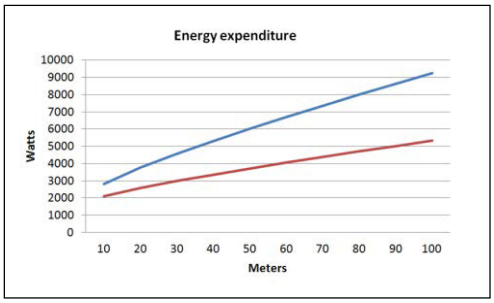

Fig.12 Energy consumption by the battery

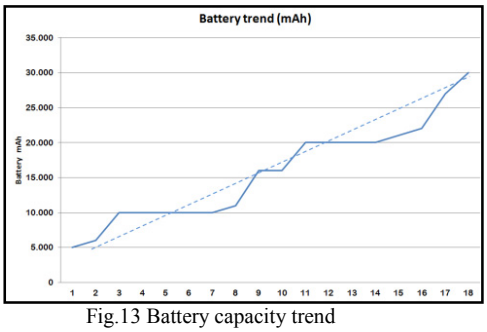

Fig.13 Battery capacity trend

The power requirement shown in Fig 12 must be delivered and supported by the active elements of the quadcopter; propellers, motors and battery. According to the estimated calculations exposed in the works in [16], the propellers and motors commercially available meet the requirements. However, the batteries commercially available today do not support the required work. It is expected that with the great development of LiPo batteries this can be overcome in a couple of years according to projections in Fig 13.

10. Conclusions

The use of quadcopter drones in a manufacturing plant, at the stage of assembly and/or customization of products, as proposed in this paper, will lead to a higher level of efficiency, effectiveness and productivity. This is based on the main characteristics of quadcopters, which are transporting materials in a 3D space, thus overcoming the limitations of AGVs, belt conveyors, hand trucks and others, that can only work on a plane or the floor, and in very rigid routes. Based on typical layouts that occur in many types of assembly facilities, the paper proposed in generic terms, layouts which will allow applying models to generate clusters.

A model based on a genetic algorithm was formulated in order to generate routes for transporting materials in short time, pursuing energy use optimization. These routes allowed establishing the total weight to be transported by each quadcopter both in the pickup and the delivery. Based in the latter, the power amount to be drained from the battery of every quadcopter was determined. This model will be the basis for generating a system of quadcopter fleet management.

The propeller and engine technology commercially available today for quadcopters (heavy duty), allow to have sufficient thrust to perform the operation of pickup and delivery within an assembly plant, for loads weighing not more than 20 kg. However, the major bottleneck of this technology is the ability of electric storage in batteries that do not allow operations beyond a few minutes. It is anticipated, with the great and rapid development of LiPo batteries, that this limitation can be overcome in a few years.

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