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Logistics drone problem and shortcomings

Abstract

A large Central European logistics centre that provides warehousing, picking, distribution and forwarding services to other multinational companies is looking for new innovative solutions. The company also has several large warehouses in an industrial park in Slovakia. The inventory control system currently requires substantial human resources and takes much time, rarely having real-time information about inventory and storage solutions. For this reason, drone application has been introduced for automatic scanning of stocks, and the pilot version is already being tested. However, two grave problems were encountered during the tests: the first problem was that the warehouse functions as a Faraday cage, so no GPS signals can be received. The other problem is how to maximize the power of the drone available for moving, which also requires optimum route planning. We are looking for solutions to these problems in the present article.

Keywords: drone, logistics centre, logistics, storage solutions

Introduction

The warehousing systems of logistics distribution centres, decentralization centres and service centres operate in warehouses increasingly large floor areas and heights. Also, they have to load, unload and store more substantial quantities of various products and unit loads, all of them for varying periods. Due to the rapid turnover of goods, the actual stock inventory becomes very complicated, often the inventory and the actual data differ, thus it is necessary to check the current stock regularly. Carrying out all of

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these tasks in a traditional manual way, even in the world of consumerized and smart devices, is an arduous and slow process. "There are several solutions to this problem, the application of which is greatly influenced by the size of the warehouse structure. In our study, the logistics centre has two large warehouses (62.000 m^2 and 55.000 m^2 respectively) with a single-depth five-level (full-height shelf) shelving system in which the shelf height can be halved or thirded. A shelf can hold up to three unit loads, and there is a smaller distance between the shelves next to each other. Inventory control is carried out with the help of a professional drone, the task of which is to identify and compare the unit load on each shelf with the registration data, and to indicate whether the right goods are in the right place or whether the goods can be found at all.

We studied the problem concerning the extent to which human intervention can be eliminated, and a proposed route of traversal, taking into account the ultimate power of the drone available. Such solutions are already used in several places, mainly by large multinational companies. Many excellent solutions are known, like e .g. the Eyesee system developed by the Hardis Group, which is a comprehensive drone inventory solution that includes an unmanned drone and is equipped with a system for automatically capturing and identifying barcode data which are then managed through the Amazon Web Services" (https://eyesee-drone.com/eyesee-the-inventory-drone-solution/ download 2020. 03. 10.).

Related literature

Amazon, DHL, and Workhorse, among many other companies, are intensively studying how drones can be applied to shipping activities. This new technology has encouraged the development of many mathematical models and solutions to this problem, contributing to the analysis of the potential benefits of small aircraft in the transport of goods. In particular, cooperation between drones and trucks on the day of operation can improve transport to the last mile, because routes can be planned more efficiently in terms of time and cost.

In his article, David Sacramento (Sacramento–Pisinger–Ropke 2019) formulates a mathematical model which defines a problem similar to the "travelling salesman problem" but for multiple high-capacity trucks, with time restriction and minimizing costs as an objective function. Because the optimal solution for large instances is complicated, adaptive large neighbourhood search meta-heuristics are proposed. Finally, extensive computational experiments are performed. The tests examine, among others, the benefits of incorporating a drone delivery option, comparing it to the case where all items are transported only by truck. In addition, a detailed sensitivity analysis is performed on many drone parameters which can be highly interesting.

Dhein et al. (2019) are dealing with the problem of finding routes for several crewless aircraft to perform a cooperative mission, requiring communication, coordination, and situational awareness. Therefore, orbits with spatial and temporal correlation are preferred, in which an indicator is proposed to measure the variance between the orbits. This dispersion index is used as an objective function of the minimum dispersion routing problem. A search genetic algorithm is proposed as a method to solve the new routing problem, and this approach has been tested using modified reference vehicle routing problem instances. The computational results show that the approach is very successful and results in trajectories with the desired characteristics in terms of dispersion.

In article Wang and Sheu (2019) the Vehicle Routing Problem with Drones (VRPD) is investigated where trucks also carry drones. The drone can be transported by the truck, retreated to serve customers, and landed at a service centre for transportation by another truck, provided the flight distance and load capacity restrictions are realized. The problem of route planning and integrated route management for trucks and drones is much more challenging and differs from that described in classical VRP literature. An arc-based whole programming model is proposed for VRPD. Because the particular problem structure results in some limitations, it is reshaped as a routing model, and a branching and pricing algorithm is developed. In the course of dealing with the pricing sub-problem, a special network is designed that differentiates between different routes and nodes and presents an improved pulse algorithm through customized intersection and extension strategies. To mitigate the target effect resulting from the slow convergence of column generation, the alternative Lagrange lower limit is calculated, and column generation stabilization is applied.

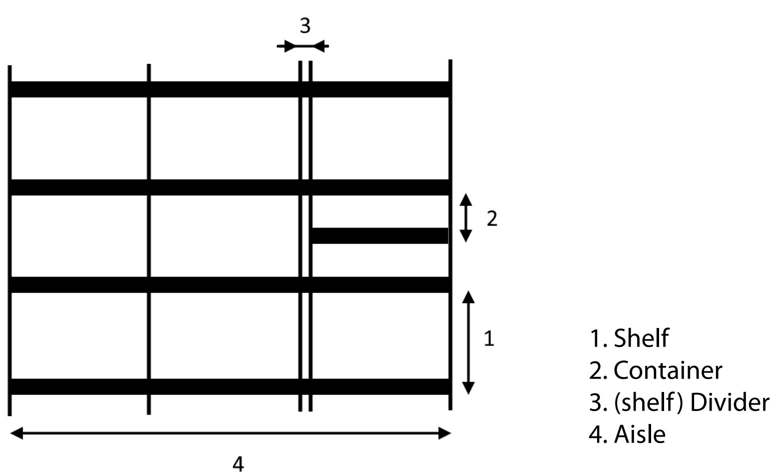
Using the branching and pricing algorithm, optimal solutions are obtained for one set of instances. The Gurobi MIP solver provides the optimal solution for 19 out of 20 cases. The average cost difference is more than 6% between the solutions that Gurobi can implement and the optimal solutions. Compared to the VRP solution, the VRPD solution not only saves an average of 20%, but all customers reduce delivery time by an average of 5 minutes, proving the efficiency of drone delivery. In the sensitivity analysis, it was observed that an advanced battery technique that doubles the flight time of drones reduces logistics costs by nearly 10%.

Schermer, Moeini and Wendt (2019) present the VRPDERO (The Vehicle Routing Problem with Drones and En Route Operations), which consists of a combination of several trucks and drones in a last-mile transport environment. The significant difference between VRPDERO and VRPD is that the former allows drones to be started and returned by vehicles in arcs; more specifically, the initiation and collection of drones may be permitted at each step of each arc. VRPDERO was formulated as a mixed-integer linear program. Then valid inequalities are suggested to improve solver performance and demonstrate the effectiveness of valid inequalities through computational experiments. However, with the help of the Gurobi Optimizer, we can optimally solve only a few small-scale problems within a reasonable runtime. Therefore, a heuristic based on the concepts of variable neighbourhood search and taboo search was introduced. Within this heuristic, as a local search operator, a drone insertion procedure was introduced and incorporated into the sharing and conquering approach. A comprehensive computational study was submitted that examined the effect of a number of problem parameters, such as production time and runtime.

Defining the problem

Companies offer several solutions for inventory with a drone. In our study, we examine the inventory problem of a large logistics service company's branch in Slovakia. An inventory monitoring system using a drone is currently being tested. To outline the issue at hand, we will use the terms as indicated in *Figure 1*:

Figure 1: *General phrases* (Self-edited figure)



During the test, we encountered the following problems:

1. The first problem is the need for manual intervention, or ideally the implementation of fully automatic operation. This problem is caused by the fact that the warehouse under investigation acts as a Faraday cage, so neither GPS nor Galileo signals are received; thus, the drone cannot be controlled via GPS position. For this reason, positioning can only be accomplished by tracking the movement of the drone. (The applied drone includes a proximity sensor, a gyroscope, a camera, and a GPS receiver.) We need to know the direction and direction of the spatial velocity vector and the magnitude of the drone during the whole operating time. Another problem is that acceleration and deceleration are to be considered. All three coordinates are required because monitoring vertical and horizontal movement is essential for drone battery capacity utilization.

   The problem is the result of the uniqueness of the drone's movement. The fact that there are no stops and starts in the case of empty containers (since the drone has distance detection, thus it knows that the container is empty) complicates the situation as it passes through them faster, but it needs approximating and receding motion to detect and photo the QR codes of non-empty containers which will cause the horizontal velocity vector of the drone shelving system to be smaller than expected.
2. Unit loads placed on shelves have QR code identifiers at the height of at least one meter that the system must be able to identify (scan) and interpret. This can only be solved without error if the drone stops after finding the QR code and takes a photo in the streamed image stream that can be interpreted by the scanner software of the management device (tablet). The system must recognize empty containers, so there is no stopping. Furthermore, it is important to note that when loading unit loads, they are placed at slightly different depths relative to each other on the shelf.
3. The third problem is the optimization of the drone route, which is vital because it is advisable to identify and process as many containers (shelves) as possible during a "flight". This is not necessarily the shortest path. It is possible that in the shortest distance many changes of direction will have to be made, there will be much deceleration, rotation and acceleration, possibly ascent all of which will significantly increase the energy uptake of the drone, thus reducing the time spent in the "air".

Solving the above problems is crucial for the logistics centre. In this article, we are looking for a solution to the first two (related) issues.

Methodology

The first thing to look at is drone movement and object recognition – in our case, QR code recognition. A similar problem is analysed by Jácome et al. (2020) concerning the problem they are investigating in their study, i. e. the target tracking of a flying drone in a defined closed area – which goes beyond our problem because their goal was to recognize the target and choose the speed, but it overlaps our field of interest. They decided on the Fuzzy solution, which is a viable path for us as well. In many cases the position of the QR code within a given location is not clear, and unfortunately, the camera does not see it in all cases. For this reason, we will also need a fuzzy control after the primary and deterministic movement. It can also be applied to differences due to columns. The study by Álvarez, Aguilera, and Arand (2020) presents a solution appropriate for us, too. Although it requires less hardware investment, it solves the positioning of the drone in a GPS-free environment with robotics by applying it to a ToF camera used in self-guidance mode. The camera is mounted on the ceiling, and it performs the positioning of the drone in the x, y directions while the height changes. Valuable technical solutions are presented here, as they prevent the interference caused by the rotors. Because of the Gaussian function-based filtering they provide, it is capable of accurate position analysis in 3D. The article also provides an exact algorithm as a solution. Another methodology to consider for closed-area drone control is presented in the study by Li et al. (2018).The authors use a voxel model and perform two types of route calculations, one for the shortest route and the other for the cheapest route. Their problem is mainly solved through obstacle avoidance image analysis, for which A. Rosenfeld and J. L. Pfaltz (1968) proposed the distance transformation method for an abnormal image in their fundamental work. In our case, the obstacles are the shelves, which are assumed to be fixed in the current solution, although it is problematic because it can change. In their case, it keeps the drone safe from the obstacle within a safe but effective distance. Another article suggests a search for known trajectory options Dhein et al. (2019). Their proposal uses a genetic algorithm, which would be very useful for us in choosing the optimal viable path. A randomly generated greedy algorithm selects the initial population. RFID based. For us, the above solutions are all helpful, but they do not provide the exact solution for the given possibilities.

Fuzzy and GA solutions, on the other hand, can be a great help in our case. For accurate positioning, we try to determine the indoor position based on 3D motion, which is good because the speed change can be handled discreetly, considering the average speed between the given measured positions. The motion is made up of two components, a deterministic motion, and a controlled motion.

The model of the problem

The data of the shelving system can be summarized as follows. There are three sizes of locations: 210 cm (full), 140 cm (3/4) and 100 cm (half) high (this includes the cross bin on which the pallet is placed). Each location is 97 cm wide (including the legs of the shelving system on average).

The vertical distribution of the shelving system varies significantly between 5 full and 9 halves. Some rows are the same throughout, but others differ from one shelf to the other. A shelf can hold 3 pallets, so at least 3 pallets are at the same height.

The vertical distribution of the adjacent shelf may be different.

There are 101 pallets on one aisle (horizontal row) (31 shelves + 2 gateways that are 4 pallets wide).

We first treat it as a 2D problem, i. e., consider a row of shelves. Of course, this does not mean that you do not have to move vertically, as the different heights of QR codes and split shelves require vertical movement. Furthermore, we included the simplification in the initial model that the QR code can be decoded (recognized) from the height of the bisector.

Let **D**; denote an n-dimensional vector, where n is the number of shelves in a given row, and **H** $n \times m$ the matrix which is the number of containers on the shelf.

Let **D**(i) denote the $i > 1$ distance of the right edge of the container from $i - 1$. This data can be uploaded in the database of the logistics service centre; the drone moves through the row from right to left.

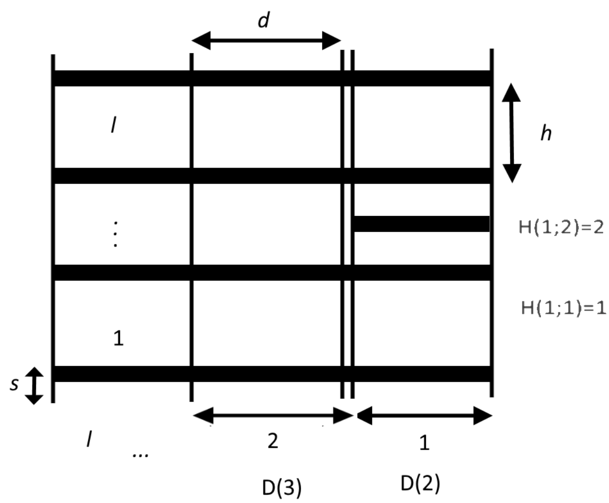
Let **H**(i, j) denote how many containers are *on the j shelf of the i* shelf column, in this case, it can be a natural number between 1–4. It plays a role in deciding whether to make a vertical movement on a given shelf to access a QR code or not (see *Figure 2*).

Furthermore:

- h denotes total shelf height,
- d denotes the shelf width,
- k is the total number of shelves vertically in the shelving system,

- s is the level of the first shelf,
- l is the number of vertical shelf columns in the shelving system.

Figure 2: *Representation of the model elements*



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It is advisable to start the movement of the drone in an aisle from the highest point because ideally, it only needs to rise once. At the end of the rows, all you have to do is descend, which is a much more energy-saving solution. At the beginning of the procedure, the drone is at the right edge of the shelving system, at floor level. The first movement is a vertical rise to the centre height of the top-level container at the edge of the shelf.

$$H_1 = s + (k-1)h + \left\{(\mathbf{H}(1;k) - 1) + \frac{1}{2}\right\}\frac{h}{\mathbf{H}(1;k)}$$

(The components are: the deviation from the floor level of the first shelf, the corresponding rise to the given shelf-number in the given shelf column, and the position of the top of the container's top shelf.)

The vertical position can thus be limited. The next decision to make is where to position the drone horizontally. Unfortunately, it is totally uncertain where the QR code label is, it simply depends on where the worker placed it. Therefore, start the drone to the left and observe the speed at which it recognizes the QR code, taking into account the acceleration of the horizontal length (distance) to the QR code:

$$\delta = \frac{a}{2}t_1^2 + at_1t_2 + \Delta t(a)$$

where t is the flight time to the QR code, t1 is the acceleration time, t2 is the time to reach the end of the shelf

$$t_2 = \begin{cases} (t - t_1) \text{ if } t > t_1 \\ \quad \text{or } 0 \end{cases}$$

and $\Delta \boldsymbol{t}(\boldsymbol{at}_1)$ is the QR code recognition inertia distance from the drone speed. You can then move in two ways, depending on the current shelf allocation and the adjacent shelf allocation. If $\boldsymbol{H}(\boldsymbol{i}+\mathbf{1}; \boldsymbol{j})=\boldsymbol{H}(\boldsymbol{i}; \boldsymbol{j})$ is valid for the current i and $i + 1$ shelves, then it is expedient to perform a horizontal movement $\boldsymbol{D}(\boldsymbol{i}+\mathbf{1})$ if $\boldsymbol{i}+\mathbf{1}\leq\boldsymbol{l}$.

If one of the two conditions is not true, then x – a reduction – must be made, that is, if we are not in the bottom line, to the top container's centre height position from the shelf below, which can be easily calculated. If the other condition is not true, i. e. we did not reach the end of the corridor, and a wider shelf column, then the movement must be positioned by halving the above movement in view of that distance.

The above procedure seems simple enough, yet it cannot be applied – in this warehouse – flawlessly. Firstly, due to unreliable acceleration and deceleration conditions, secondly, due to inertia, and thirdly, due to the non-uniform placement of the QR code. Based on a trial test, the drone required very little manual tuning (although it still needed some) in case of uniform QR code application. It can be established that accurate automatic positioning cannot be achieved with the current drone type until the shelving system is not arranged uniformly, and the QR code is not affixed in a well-defined manner.

Summary and proposal

During the analysis and modelling of the problem, it became apparent that with the current logistics solutions and the applied drone, the automation of the inventory management process cannot be solved. Our suggestions are summarized below.

1. QR codes should be placed on unit loads in a well-defined standard location; its position should be determined from the lower right corner of the load in both directions. It may be possible to indicate the location of this with a laser pointer or on the packaging device itself (as we are dealing with hire storage, the latter is difficult to achieve).

2. A line-code identifier should be placed on the shelving system for each section (both vertically and horizontally), which would improve positioning and provide basic information about the column.
3. This proposal is costlier but would significantly increase efficiency. If ToF cameras were used, they would also help with precise positioning and directions of movement.
4. The latter would also be effective if more than one "professional" drones with available sensors were used. (Due to their rapid development, we do not wish to suggest any type of drone or type of sensors presently.) Expectations for the drone: long operating time, accurate gyroscopic positioning, real-time speed feedback, the camera should ensure accurate code reading while on the move.

In summary, it is possible to improve routing, better utilize drone capacity, and provide a semi-automatic solution to the current situation with the help of an operator. This is a much more effective solution than the "visual" one used previously.

References

Álvarez, J. –Aguilera, T. – Arand, F. J. (2020). Precise drone location and tracking by adaptive matched filtering from a top-view ToF camera. Expert Systems with Applications, 141, Article 112989.

Dhein, G. – Zanetti, M. S. – Olinto Araújo, C. B. – Cardoso, G. (2019). Minimizing dispersion in multiple drone routing. *Computers & Operations Research,* 109, 28–42. https://eyesee-drone.com/eyesee-the-inventory-drone-solution/ (download 2020. 03.10.).

Jácome, R. N. – Huertas, H. L. – Procel, P. C. – Garcés, A. G. (2020). Fuzzy logic for speed control in object tracking inside a restricted area using a drone. *Smart Innovation, Systems and Technologies,* 152, 135–145.

Li, F. – Zlatanova, S. – Koopman, M. – Xueying Bai (2018): Universal path planning for an indoor drone. *Automation in Construction,* 95, 275–283.

Rosenfeld, A. – Pfaltz, L. F. (1968). Distance functions on digital pictures. *Pattern Recognition,* (**1**)1, 33–61.

Sacramento, D. – Pisinger, D. – Ropke, S. (2019). An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones. *Transportation Research,* Part C, 102, 289–315.

Schermer, D. – Moeini, M. – Wendt, O. (2019). A hybrid VNS/Tabu search algorithm for solving the vehicle routing problem with drones and en route operations. *Computers and Operations Research,* 109, 134–158

Wang, Z. – Sheu, J. B. (2019). Vehicle routing problem with drones. *Transportation Research,* Part B, 122, 350–364.