Study of Optimization Problems Associated With Technical Implementation of Drones in the Post-Pandemic Society

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Abstract

As the world faces the pandemic of COVID-19, how to *minimize* human contact becomes an imperative issue for governments short of shutting down their entire economies or closing borders with their neighboring countries. Several new technologies have emerged in this time of need, particularly the drone technology, which has been used extensively in disaster reliefs, warehouse operations and security monitoring. In this research, several optimization problems related to drone technology were surveyed, especially the facility location problem. Moreover, the optimization modelers—LINGO and PuLP—were used to solve the optimization problem and compared in terms of their performance. Even though both performed the same in terms of solution quality, PuLP performed better with respect to the execution time. Overall, this paper offers a complete view of drone applications in this world facing the pandemic, drone optimization issues and implementation for solving an optimization problem.

Keywords
COVID-19, Drones, Optimization, Unmanned Aerial Vehicle (UAV), and Facility Location Problem.

1. Introduction
Drones or Unmanned Aerial Vehicle (UAV) has been used and explored extensively lately, especially in the logistics field. The drone market has been projected to grow by $29 billion by 2027 with an annual growth rate of almost 20% (MarketsandMarkets 2019, Warla et al. 2021). Moreover, reports by the Federal Aviation Agency in the United States forecasted that the increase of small drones from 1.2 million in 2018 to 1.4 million in 2023, annual growth of 2.2 percent (FAA 2019). Drones are becoming popular because they are able to fly into and out of remote or other inaccessible regions without impacting ground operations, avoid obstacles in indoor facility layouts, land precisely and potentially travel in fleets (Warla et al. 2021). A drone is defined as "powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely…" (Dictionary of Military and Associated Terms 2005) For small UAVs, the commonly identified UAV design is the *quadcopter*, which consists of four rotors providing great maneuverability and hovering capability. Thanks to recent advances in visual based navigation and sensors, drones are able to navigate outdoor as well as indoor. Reported in the white paper of "Applications of drones in warehouse operations", Warla et al. (2021) pointed that drones are most promising in those three warehouse operations: inventory management, intralogistics, inspection and surveillance. Particularly in the field of intralogistics, drones have great potential to be used for carrying items by following predefined flight paths even though they may be limited by the weight of payload, movements and navigation.

The newly discovered Coronavirus disease 2019 (COVID-19), an infectious disease characterized by fever, cough and severe respiratory problems, made its grim entrance in December 2019 in China and spread worldwide since. With its high transmission capability, the virus spreads easily among people. In Europe, national governments have shut down borders to prevent influx of migrants from other countries; consequently, the global supply chain and transportation networks have been severely disrupted (Kunovjanek and Wankmuller 2021).

Kim (2021), the current secretary-general of International Transport Forum (ITF), especially pointed out the new technologies such as “drones” will play increasingly important roles made possible by the *minimum human contact* that current situation—pandemic outbreaks—demands. With this aim, the world has seen a boost to the use of drones to make medicine delivery, monitor social distancing and broadcast public announcements (International Transport Forum 2021). Moreover, according to UNICEF Supply Chain Strengthening Centre (2021), in addition to medicine delivery and space monitoring, drones may also participate in aerial spraying of disinfectants in contaminated places (Supply Chain Strengthening Centre 2021). In the UNICEF report, they also recommend building a “support system and enabling environment” including establishing procurement algorithms based on most cost-efficient service with respect to quality, agility, sustainability, compliance and other key elements.

Several government, research institutions and private companies have come up with drone-based solutions to help deliver supplies or monitor crowds in this post-pandemic era. The UniSA team at the University of South Australia has deployed a specialized drone, equipped with a specialized sensor and computer vision system, which can monitor “temperature, heart and respiratory rates, as well as detect people sneezing and coughing in crowds”. (Gibson 2020) Zipline—a flight company in the US—has been flying drones to deliver personal protective equipment and COVID-19 tests including blood products and vaccines during the pandemic in North Carolina, USA (Porter 2021). Jorge et al. (2021) conducted the experiments of testing a spraying drone system for disinfection purposes in an outdoor setting. Then the spraying methodology is compared with humans with a spraying backpack or spraying truck. The results indicated that drones appear as reliable and efficient—they provide highly accurate spraying, move faster than humans, and reach more places than spraying trucks. Euchi (2021) has presented a summary of the “medical drone manufacturing” with the emphasis of logistics applications in healthcare in light of the pandemic.

Nevertheless, the studies of operations research related to the technical aspects of drone technologies are still far and between. Computers & Operations Research especially presented a special issue, “Computational Operations Research for Drone Systems”, in the past year. According to the editors, “techniques from operations research along with efficient and effective computational approaches are necessary to properly implement these complex systems” (Murray and Smith 2019). Therefore, the focus of this research is to investigate the optimization problems and methodologies for solving those to help with the future implementation of “smart” and “autonomous” drone technologies without the remote control of a human operator.

1.1 Objectives

The paper investigates the optimization problems and methodologies associated with unmanned aerial vehicles which have been increasingly relied on by the general society facing the global pandemic. For the rest of the paper the operations research problems, their relevance to the UAVs, as well as their mathematical models and solution implementation will be discussed.

2. Literature Review

In this section, the optimization problems of operations research related to UAVs are discussed. Among those, we present the multiple quadratic assignment (QAP) problem, hub-location and routing and facility location problem, which are generally investigated because they are mostly related to essential activities of drone planning: hub assignment and route charting.

2.1 QAP Problem

The optimization of various communication flows among a drone fleet has been mapped to the quadratic assignment problem, a classical NP-hard combinatorial optimization problem (Day et al. 2003, Kleeman et al. 2004).

The mathematical model of quadratic assignment problem can be seen in Equation (1):

$$C(\pi) = \pi \in P(n) min \sum_{i=1}^{n} \quad \sum_{j=1}^{n} \quad a_{ijb_{\pi i \pi j}} \tag{1}$$

where *n* is the number of objects or locations, a_{ij} is the distance between locations *i* and *j*; b_{ij} is the flow from object *i* to object *j*; π_i and $\pi_j$provide the locations of object *i* and *j*, respectively, in permutation $\pi \in P(n)$ where *P*(*n*) is all the solution search space of QAP.

Day et al. (2003) investigated multi-objective quadratic assignment problem (*mQAP*) of military UAVs through minimizing the multiple communication flows (e.g., reconnaissance information, target information and status message, etc.) transmitted among those planes. To solve the *mQAP* problem, they used the following mathematical model and equations presented in Equations (2) and (3):

$$minimize\{C(\pi)\} = \{C^1(\pi), C^2(\pi), \ldots, C^{2m}(\pi)\} \tag{2}$$

$$C^k(\pi) = x \in P(n) min \sum_{i=1}^{n} \quad \sum_{j=1}^{n} \quad a_{ij} b_{\pi i \pi j}^{k}, k \in 1 \ldots m \tag{3}$$

Equation (2) represents minimizing all the objectives in an *mQAP* problem by forming the Pareto front. All the variables in Equation (3) are the same as in a typical QAP math model explained already in Equation (1).

They proposed an algorithmic approach to solve the *mQaP*—UAV communication and mission success problem—through the meta-heuristic of Multi-Objective fast messy Genetic Algorithm (MOMGA-II) (Zydallis 2003), which is extended from the multi-objective evolutionary algorithms (MOEAs) (Goldberg and Deb 1989). They verified the effectiveness of the newly proposed algorithm against the data set from existing literature, namely those generated by Knowles and Corne (2003). Their results indicated most of Pareto optimal points at the Pareto front were found during their experimentation.

One year later in another conference, Kleeman et al. (2004) presented the parallel computing version of the MOMGA-II and compared the number of processors in terms of speedup and efficiency. Speedup represents the degree of speed increase when it comes to the parallel processing versus serial processing; on the other hand, efficiency measures the proportion of actual processing time versus idle time during parallel processing. The authors have discovered that increasing the number of processors corresponds to linear speedup when compared with computing in the serial version.

2.2 Hub-location and Routing

P-Hub location problem (HLP) is a *NP-hard* problem often discussed in the fields of communication networks, airline passenger flow and parcel delivery networks. The problem was first formulated by O'Kelly (1987) as a "quadratic integer program with a non convex objective function". The HLP problem is presented with *n* nodes which interact through a set of fully interconnected hubs (transit nodes); a subset of *n* nodes, *p*, is designated as transit nodes. The transit nodes are uncapacitated—that is, no limitation exists on the number of nodes connecting to a single transit node. However, nodes can only be allocated *at most* to a given hub for this single allocation problem. Because of the size of its solution space, the HLP problem is considered to be a *NP-hard* problem.

The following presents the symbols, objective function, constraints and their description used in the mathematical model.

Symbol Notation

i:	Node i
j:	Node j
k:	Transit node k
m:	Transit node m
f_{ij}:	Amount of data flow between nodes i and j
c_{ij}:	Cost of communication for transferring a unit of data flow between i and j
x_{ij}:	Binary variable where x_{ij} equals to 1 if node i is assigned to hub j, and 0, otherwise
x_{jj}:	Transit node (node j is assigned to itself)

Objective Function

$$Minimize \qquad Z = \sum_i \sum_j f_{ij} (\lambda (\sum_k x_{ik} c_{ik} + \sum_m x_{jm} c_{jm}) + \alpha \sum_k \sum_m x_{ik} x_{jm} c_{km}) \tag{4}$$

Constraints

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$$(n - p + 1) x_{jj} - \sum_i x_{ij} \geq 0 \;\; \forall j \tag{5}$$

$$\sum_j x_{ij} = 1 \;\; \forall i \tag{6}$$

$$\sum_j x_{jj} = p \tag{7}$$

$$x_{ij} = 0 \quad or \quad 1 \tag{8}$$

The objective of the HLP is to minimize the total *communication costs* among all pairs of access nodes, which rely on their corresponding transit nodes to route the data as indicated by Equation (4). Constraint (5) ensures that access nodes could only be allocated to the transit nodes. Constraint (6) states that all access nodes can only be assigned to one and only one transit node. Constraint (7) states that only a certain number of transit nodes will be located. Equation (8) indicates that x_{ij} is a binary variable.

In HLP, Sensors or actuators equipped on drones are generally known as the “access nodes”, which “represent source and destination of traffic demands but cannot be directly connected”; hubs, access points, base stations are known as “transit nodes” , which are “typically fully connected, do not generate or attract traffic demands but collect traffic from access nodes and route them through the network.” (He et al. 2009) Figure 1 depicts that the data is routed from access node *i* via transit nodes *k* and *m* and finally to node *j*; the route is indicated by the thick dashed line. How to minimize the total communication cost for all pairs of access nodes is the main objective of this research. The communication cost may come in the forms of fixed costs, “namely the costs of opening and equipping a transit node in a given site” and connection costs, “namely the costs of installing on each edge the capacity needed to route the traffic on the edge itself.” (Carello et al. 2004)

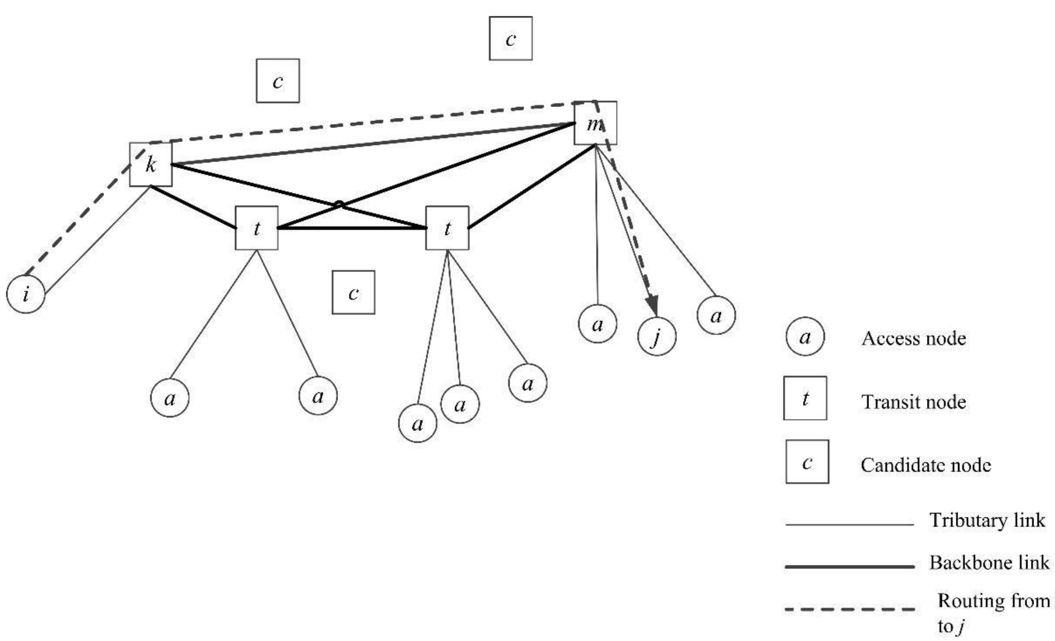

Figure 1. Architecture of hub location problem in a communication network (Carello et al. 2004)

Sarıçiçek and Akkuş (2015) investigated the possible locations for hubs of UAVs along country borders in Turkey—a critical national issue in light of drones' roles in today's high-tech warfare. They concentrated on the tasks of picking hubs from a selection of airports run by the General Directorate of State Airports Authority of Turkey, assigning hubs' demand points, and charting best routes to each hub. The authors divided the work into two stages: (1) finding the locations of the hubs for assigning the UAVs and (2) finding the best routes for each hub. They used ELECTRE—a multi-criteria decision-making tool for hub selection—to generate multiple input parameters for the problem and solve through the CPLEX of the GAMS program to determine the optimizing results for hub assignment and route charting.

2.3 Facility Location Problem

Yeghikyan (2020) envisioned the proliferation of drones in an urban setting where the fleets of drones may eventually impact buildings designed and built. The drones need the docking stations for recharging and as hubs for goods pickup. According to him, several issues of drones need to be addressed: (1) where one places the drones' docking stations; (2) how many of them are assigned to each docking station; (3) what capacity does each docking station have. Therefore, the researcher found that the drones' docking station issues can be modeled as the *capacitated facility location* problem with a slight constraint difference from Holmberg et al. (1999), which is addressed below:

Symbols or Variables:

- n: Number of customers
- m: Number of docking stations
- i: Individual customer
- j: Individual docking station
- x_{ij}: A fraction of demand of client i that is satisfied from a facility at j
- d_i: Demand by an individual customer
- y_j: A binary variable where y_j=1 representing a drone station is installed at location j; y_j=0, otherwise.
- M_j: The capacity of a drone station
- f_j: Installation cost of a drone station
- c_{ij}: Operation cost of a drone station j assigned to customer i

Objective Function:

$$Minimize\ Z = \sum_{j=1}^{M} f_j y_j + \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} x_{ij} \tag{9}$$

Constraints:

$\sum_{j=1}^{M} x_{ij} = d_i$;

$$\sum_{i=1}^{n} x_{ij} = d_i \qquad \text{for } i = 1,\ldots,n \tag{10}$$
$$\sum_{i=1}^{n} x_{ij} \le M_j y_j \qquad \text{for } j = 1,\ldots,m \tag{11}$$
$$x_{ij} \ge 0 \qquad \text{for } i = 1,\ldots,n;\ j = 1,\ldots,m \tag{12}$$
$$y_j \in \{0,1\} \qquad \text{for } j = 1,\ldots,m \tag{13}$$

The objective of the drone docking station location problem is to minimize the total cost of drone station installation costs and drone operation costs as shown in Equation (9). Equation (10) represents the first constraint set which requires each customer's demand must be satisfied. Equation (11) represents the second constraint where the fractioned service provided by a drone station is limited by its assigned capacity: if drone station j is installed, its capacity restriction is considered; if not, a customer's demand is not satisfied—x_{ij} is 0. Equation (12) states that x_{ij} must be a positive number, while Equation (13) confirms y_j as a binary variable.

Furthermore, Lynskey et al. (2019) investigated the management of landing and take-off areas of drones. They reported that through the optimization of assigning drones to "drone ports" as a facility location problem and travel salesman problem for finding drones' shortest route to travel those hubs, their proposed solution have achieved the objectives of minimizing the average distances traveled by drones between potential port locations and overall energy consumption by drones.

Chauhan et al. (2019) also investigated the range constrained drones by modeling the phenomenon as a maximum capacitated facility location problem with Drones (MCFLPD). They solved the proposed model through three methods: Gurobi solver—an optimization package—through the Python interface, a greedy heuristic implemented in Python and a three stage heuristic solved through Gurobi. They contributed to the academics by creating a new integer programming model to locate drone hubs to meet customers' demands located at geographically distributed areas.

Based on those papers reviewed, the *facility location problem* emerged as the most popular math model. The fact may reflect that drone planning is most relevant to the hub assignment, which is imperative for drone recharging and goods pickup, as the number of drones increases exponentially.

3. Methods

The entire research follows the four-stage decision-making process: (1) Formulate, (2) Model, (3) Optimize and (4) Implement (Talbi 2009). This process is shown below in Figure 2. The process can be linear, spiral or cascade.

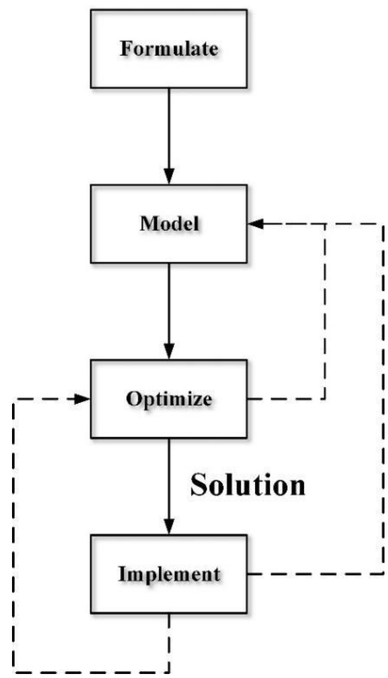

Figure 2. Four-stage decision-making process (Talbi 2009)

For optimization, the research uses both *LINGO* (Linear, Integer, Nonlinear, and Global Optimization) version 13.0 and *PuLP* optimizer version 2.4 to solve the facility location problem defined by Yeghikyan (2020). The reasons for using two approaches for solving the optimization problems are twofold: (1) the confirmation of answers by two optimization tools and (2) evaluation of performance by two popular optimization packages.

LINGO is an integrated optimization package designed to solve linear, non-linear (convex and nonconvex/global), quadratic problems and so on, equipped with its own language for expressing mathematical models and environment for building and editing problems (Lindo Systems Inc. 2021). It contains algorithms such as mixed integer linear program, branch-and-bound, and more.

PuLP optimizer is an open-source linear programming (LP) package, written in Python programming language and packed with many industry-standard solvers (Sarkar 2019, Roy and Mitchell 2020). It also can be integrated with other open source and commercial LP modelers (Roy and Mitchell 2020).

4. Data Collection

The test dataset are obtained from (Holmberg et al. 1999), with the title of "*An exact algorithm for the capacitated facility location problems with single sourcing* " and available from the website: https://or-brescia.unibs.it/instances/instances_sscflp (Operational Research Group - University of Brescia 2021). Holmberg's data set consists of the following sizes related to number of facilities *m* and customers *n*, respectively, as shown in Table 1.

Table 1. Sizes of test data sets

Set	Problems	*m*	*n*
1	p1-p12	10	50
2	p13-p24	20	50
3	p25-p40	30	150
4	p41-p55	10-30	70-100
5	p56-p71	30	200

5. Results and Discussion

The execution results including the solution qualities and computation time are presented in subsection 5.1.

5.1 Numerical Results

The execution results of LINGO and PuLP optimizers are presented below in Table 2. A selection of ten problems, which represent various sizes from all sets, are derived from Holmberg's data set. Those problems are listed under the **Problem** column in Table 2. The column **Objective Function Value** columns contain the solution qualities executed by both optimizers. The column **Execution Time** in the units of milliseconds (*ms*) is shown in column 3. The last column, OFV Δ %, represents the % of differences between two optimizers. Since both optimizers obtained the optimal results, less than three runs of algorithmic execution for each problem are performed. In terms of solution quality, both performed equally well with the same results. The delta % between two optimizers are 0.

Table 2. Execution results of Lingo and PuLP optimizers

Problem	Objective Function Value		Execution Time (ms)		OFV Δ %
	LINGO	PuLP	LINGO	PuLP	
p1	141630	141630	30	30	0
p2	140316	140316	30	30	0
p3	142316	142316	30	30	0
p13	190647	190647	1000	50	0
p14	187795	187795	1000	50	0
p15	191795	191795	1000	60	0
p25	172141	172141	5000	290	0
p26	170853	170853	4000	350	0
p41	49955	49955	1000	50	0
P56	254657	284657	2000	260	0

In terms of the execution time between Lingo and PuLP optimization modelers, it can be easily seen that PuLP performs much better than Lingo with much less execution time. The graphical results are shown in Figure 3. It could be related to less overhead associated with PuLP, which is written in the Python language while Lingo has more overhead such as its modeling files with the extension of .lg4 and executes two algorithms—Mixed Integer Linear Programming and Brand-and-Bound— for each run.

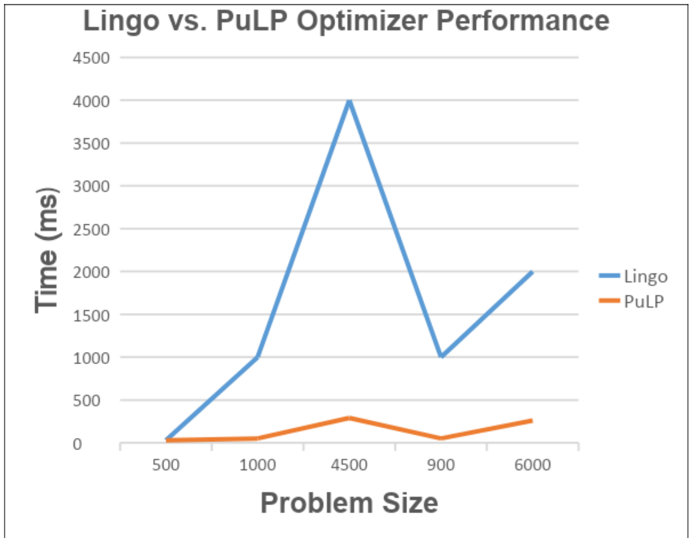

Figure 3. Execution time comparison of Lingo and PuLP

6. Conclusion

The pandemic of COVID-19 has devastated the world since the beginning of 2020; many nations have chosen the approach of closing the borders and enforcing curfew to combat the spread of virus from person to person. However, the past history has taught us that the closing is the last measure to take because it could easily result in loss of trades and cause the downturn of economies. The emergence of drone technologies in recent years may help the society to minimize human contact while allowing the transport of goods to continue. Combined with artificial intelligence, drone technology may one day provide services to people far beyond their imagination, but at the current moment many technical issues related to drones or UAVs are still waiting to be resolved and investigated.

The research paper presents the optimization problems in operations research related to drone technologies, namely the multiple quadratic assignment, hub location and facility location problems. Moreover, the researchers have utilized two popular optimization modelers: LINGO 13.0 and PuLP 2.4 to solve facility location problems and determine their performance in terms of solution qualities and time performance. The results indicated both performed the same when it comes to objective function values; nevertheless, PuLP performed better than LINGO when the execution time—i.e., the amount of CPU time taken to solve problems—was concerned.

The results provide the groundwork of optimization problems related to drone technologies for future researchers to build on. Besides, the popular optimization tools are compared and investigated. In other words, this investigation offers the end-to-end consideration of drone optimization issues from problems to solution implementation and contributes one's effort to this new, exciting field of drone technology.

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