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SHEPHERD: a Digital Blueprint for Drone Based Logistic Networks

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Abstract

Drone Logistic Network is an emerging technology in the sector of logistic support with potential applications in goods delivery, postal shipping, healthcare networks, emergency response, etc. This highly complex system often involves different design requirements along with multiple objective functions such as time for delivery, capital and operational costs, network efficiency etc. Moreover, we need to ensure the reliability, resilience, and safety of the designed network. This required the need to simulate contingencies scenarios during the network design in order to evaluate the performances and functionalities of the proposed network. Here, we present `SHEPHERD', a digital blueprint model of a drone logistic network for supporting the national healthcare system (NHS) of Scotland. SHEPHERD is a collection of tools and models for network design, planning and scheduling. The paper will give an overview of the models, the computational strategies for strategic and tactical decision making implemented in SHEPHERD and some selected results demonstrating the applicability of the tool.

Keywords: digital twin, drone, reliability, resilience, logistic network, healthcare, modelling and simulation

1. Introduction

In recent years, the effectiveness of healthcare systems has seen significant improvement through the implementation of distributed healthcare networks. The transport of microbiological specimens including blood cultures by drone was studied in (Amukele, 2016). Successful flight tests for medical delivery have been conducted in Spain as well (drones5010013). Additional study on the impact of drone transportation on biological samples was explored in (Lippi, 2016), revealing no adverse effects for turnaround times of less than 4 hours. Moreover, feasibility of drone logistic networks for delivering medical goods was observed by Leonardo and Telespazio (Leonardo, 2020) near Rome, Italy and by Matternet (Metternet, 2020) in Berlin, Germany. Similar initiatives were undertaken in Switzerland with Swiss Post involving the transportation of laboratory samples between two hospitals (Swisspost, 2018). The UK government is also exploring the possibility of an autonomous Drone Logistic Network to facilitate the delivery of medical equipment and assistance to remote areas. As part of these initiatives, the project `CAELUS' (Care & Equity – Healthcare Logistics UAS Scotland) was sanctioned by the UK Industrial Strategy Future Flight Challenge Fund (Project CAELUS, 2022). To achieve this goal in CAELUS, we are developing SHEPHERD to understand the nuances of a drone logistic network in the context of Scotland. It combines Digital Twin models of the complex networked system with a set of robust optimisation and uncertainty quantification tools, serving a dual purpose: the design of a drone delivery network (strategic use) and its optimal operation (tactical use).

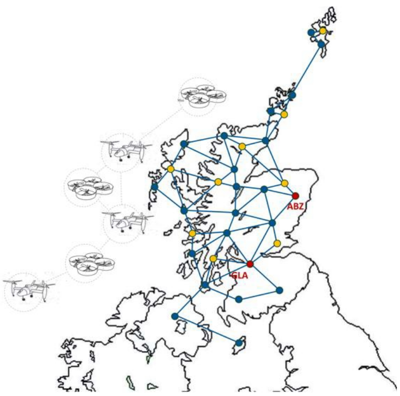
The strategic use of SHEPHERD involves the design of the entire Drone Logistic Network optimised with respect to the key performance indicators defined by stakeholders. This is done prior to the construction of the physical network and is executed entirely in a virtual environment simulation. The design problem is translated into a multi-objective generative network optimisation (Gao, 2019), considering indicators such as capital and operational costs, delivery time, network reliability and resilience to unexpected events (Filippi, 2022). The tactical aspect of SHEPHERD is concerned with the network operational problem. That is the online simulation of the Digital Twin during the use of the physical Drone Logistic Network to find optimal planning and scheduling. SHEPHERD is also utilised to simulate various flight scenarios affected under uncertain conditions (Basu, 2023) and determine optimal actions. This paper further advances what was proposed by the authors in ((Filippi, 2023).

1.1. Problem definition: healthcare drone-based logistics in/for Scotland

The uneven distribution of Scotland's population and geographical constraints as shown in

Fig. 1 poses a challenge for ensuring equal access to essential health services. In CAELUS, we address this challenge by proposing a drone-based network, to support the distribution of medical items across Scotland efficiently. Drones however have limited payload, battery capacity, flight range and are vulnerable to adverse weather conditions. Therefore, a systemic methodology for strategic and operational network design is required to overcome the drone-specific constraints and generate a tool for dynamic optimisation of the Delivery Network System. The design should also ensure that the transported medical equipment (e.g. defibrillators), medicament (e.g. drugs) or biological items (e.g. organs, blood) satisfies the constraints in the temperature, delivery time and availability/reliability. At strategic (design) level, this Digital Blueprint should have the ability to decide optimal facility locations, resource allocation and drone routing. From a tactical (operational) point of view, this needs to have a fast computation scheme of the optimal network planning/scheduling and re-planning/re-scheduling after new contingencies.

(a)



(b)

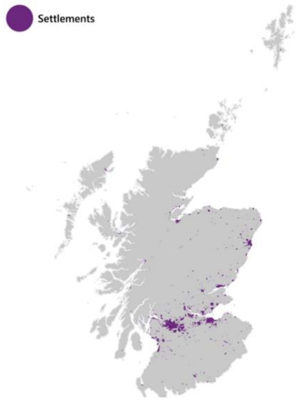


Fig. 1. Conceptual model of a drone-based delivery network as part of CAELUS project. (a) Drone-based delivery network. (b) Population settlements in Scotland.

2. SHEPHERD: a digital blueprint for drone-based delivery network

SHEPHERD is a Digital Twin for the drone-based logistic network. The digital twin comprises a set of models at varying levels of fidelity for drones; systems; sub-systems as well as the entire system-of-systems network, a set of software tools for robust optimisation, uncertainty quantification, and risk and resilience assessment, and interfaces to acquire drone telemetry, weather conditions and with drone operators. The high-fidelity models implemented in SHEPHERD offer the highest level of accuracy but at a significant computational cost that make them applicable only for off-line simulations. Low fidelity models, on the other hand, are quick to compute and they are designed to be used for assessing the effect of uncertainty in the results and for any near-real time simulation. A modular approach has been used for the digital twin framework allowing the analyses and simulation of the network with different levels of granularity and accuracy, i.e. using low fidelity models, surrogates, or high-fidelity simulations.

As a proper digital twin, SHEPHERD allows a two-way connection with the real system counterpart. It receives information from the sensors and telemetries which allows it to continuously improve the accuracy of the digital models and situational awareness. On the other hand, it represents a support decision tool by identifying optimal strategic and/or tactical decisions for the real system. SHEPHERD can act across different scales in both space (i.e., global network, regional network, single station, or link) and time (i.e., strategic and tactical/operational). Moreover, SHEPHERD also includes tools for assessing reliability and resilience of the entire network, the risk and reliability of individual flight taking into account population density, wind speed, drone characteristics and payload to ensure a smooth operation of the system.

2.1. Model descriptions

2.1.1. Network representation

The whole network is modelled as a system-of-systems given by the combination and interaction between different network components at lower levels. An agent-based simulation has been developed with this scope and is used to study the emergent behaviour of the whole complex system as the result of the interaction between different agents. For example,

Fig. 4 shows different NHS locations and laboratories and our objective is to find an optimal design to connect these locations as well as obtain a path for delivery as explained in Section 3.4.

2.1.2. Flying constraints

The design and performance of a delivery network of drones needs to consider flying restrictions such as No-Fly Zones, wind speed, temperature, and population density. No-Fly Zones are due to critical infrastructures or areas for which drones could represent or be subjected to risk and safety issues. These areas are then interdicted to potential flight paths. Different types of No-Fly Zones are possible, and the main categories are: ‘restricted’, ‘danger’, ‘prohibited’ areas. A representation of No-Fly Zones in Scotland for all the three categories is shown in where the areas are defined as a list of 2-D polygons. Within SHEPHERD, we include these No-Fly Zones as hard-constraints to optimise problems for the network design, path planning and scheduling such that no flight trajectory can intersect these polygons.

Population density is an essential factor to be considered since it affects the risk of ground impact as shown in

Fig. 1. In traditional aviation, the primary safety considerations refer to the lives and property of the crew and passengers. In contrast, the foremost safety apprehension in Unmanned Aircraft Systems (UAS) operations is the risk encompassing individuals and properties not associated with the UAS operation. New risk indicators are currently under research and development (Chengpeng, 2020).

Weather conditions (wind velocity) have significant impact on battery consumption and time of flight. They may also produce some (temporary) additional no-fly-zones due to expected wind gusts. At a tactical level, expected weather conditions are constructed based on historical data, i.e. we assume the future weather condition will be statistically equivalent to past conditions. This has been obtained based on a Gaussian Process regression based on historical data from the UK Metoffice (Metoffice, 2024). We show this in Figure 2.

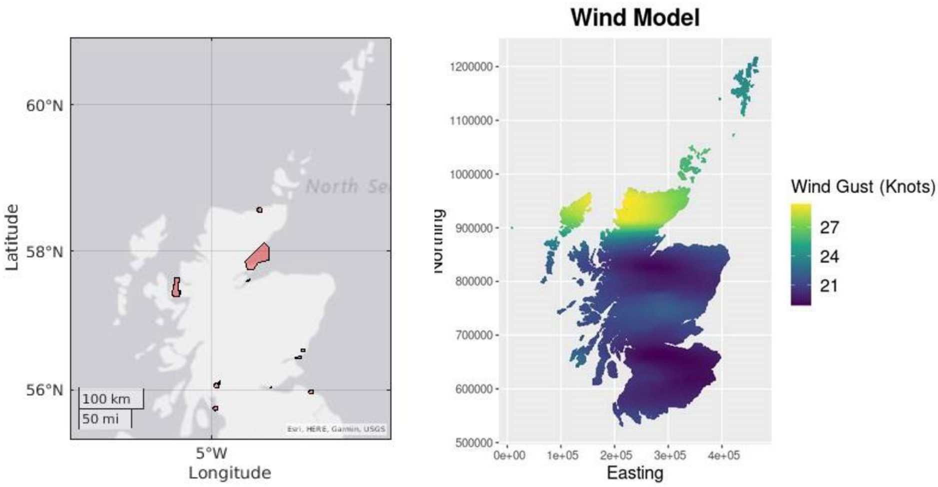


Fig. 2. Environment conditions in Scotland. (a) No FLight ZOnes. (b) Expected wind gusts.

2.1.3. Ground impact model

The calculation and minimisation of the risk of fatalities due to possible ground impact of failed drones is of fundamental importance and used within the Path Planning problem defined Sec. 3.4 and within the higher-level optimisation problems of Network Design and Network Planning and Scheduling in Sec. 3.3. The fatality risk is calculated based on ground information on population density, flight path and the expected wind speed in that area. A specific risk can be calculated for each path and alternative paths proposed to minimise the risk under different weather scenarios.

2.1.4. Payload thermal model

Temperature control of the payload is essential to satisfy the strict thermal constraints on the medical items. The temperature control system considered is a passive system that includes, as shown in Fig. 3(a) an insulating package (blue), a medical payload (orange) and a Phase Change Material, or PCM, (green). The PCM is a component which absorbs energy at the phase transition to provide cooling. A lumped mass model based on the electro-thermal analogy including thermal conduction and convection have been developed and it is shown in Fig. 3(a) as a circuit of resistors and capacitors. The model has been verified against the results from ATMOS high fidelity software from Intelsius (see Fig. 3(b)). The figure shows a particular test case where temperature of the system is propagated subjected to the external temperature dynamics predefined as a discontinuous function. Thermal properties of the package are affected by uncertainty and a set of stochastic differential equations have been then solved to simulate the temperature evolution of the external (blue) and internal (red) walls of the insulating package, the internal air (yellow), the PCM (purple) and the payload (green). The simulated payload temperature is finally compared with the higher fidelity results from Intelsius plotted in the figure as a thick line.

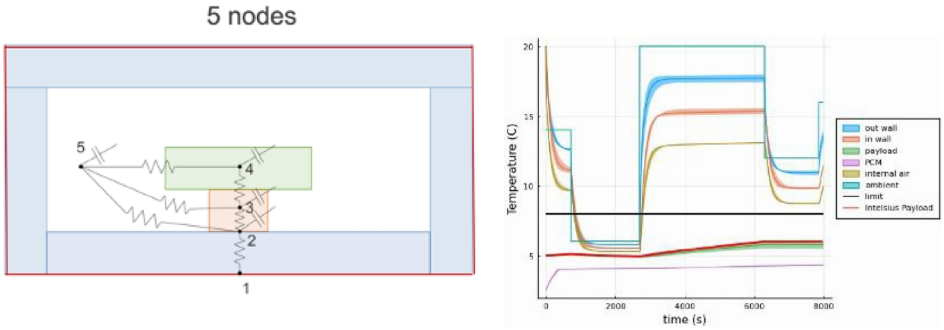


Fig. 3. Thermal System model for medical items. (a) Lumped mass model for the medical thermal system. The system is composed of an insulating package (blue), a medical payload (orange) and a Phase Change Material, or PCM (green) (b) Verification of the Strathclyde thermal model. The sub-plot shows the results for both Strathclyde model and ATMOS (thick red line).

2.1.5. Aerodynamics and flight simulation

Aerodynamics models have been developed for two representative types of Drones: a quad-rotor drone and fixed wing drone types. A PID controller has been implemented and trained for both drone types so that the drones can follow a given trajectory based on the model discussed in (Kristofer2018). Based on this high-fidelity simulator we show a flight trajectory in

Fig. 4(a). The flight dynamics and control model/simulation allow to explore not only the flight-dynamics but also, e.g., the aero-acoustics impact on the ground, that is particularly important given the regulatory restrictions overpopulated and protected areas. As an example,

Fig. 4(b) shows the aeroacoustic map for a sample flight.

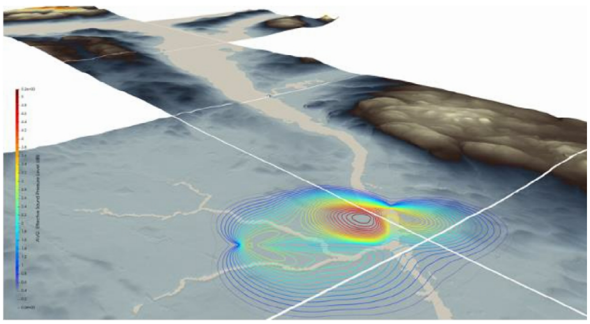


Fig. 4. Flight dynamic model. (a) Flight trajectory of a delivery. (b) Aeroacoustics map produced by a flying drone.

3. Applications

3.1 Design of drone network for Scotland

At a strategic level, the goal is to calculate a set of optimal network design configurations, in a Pareto sense for delivering medical items across NHS locations and making use of existing airports and additional charging stations for drones. This network design required the solution of a set of related problems including vehicle routing problem with heterogeneous fleet, facility location problem and resource allocation problems. The optimisation problem can be represented as follow. Consider the multi-layer graph $G(\Gamma, E^v)$ with Γ representing the set of all nodes and E^v the set of all edges:

$$E^v = \{(i,j) \mid i,j \in \Gamma, d(i,j) \leq R^v\} \tag{1}$$

where $v \in V$ is the number of layers with V the set of drone types. Consider K the set of existing stations and I the set of additional stations, such that $\Gamma = K \cup I$. Define M as the set of mission where each mission is defined by the couple of pick-up and delivery stations, (P_m, D_m). Finally, V, S^c and S^s store the information about different alternatives for drone types charging infrastructures and drone storage infrastructures respectively. The network design is a multi-objective optimisation problem for which the vector of objectives can be represented as:

$$\mathbf{f}(\mathbf{x}) = [f_1, f_2, \dots, f_m]^T \tag{2}$$

For a robust solution, uncertainty needs to be propagated to quantify specific metrics (e.g., network reliability and resilience). The delivery time and capital cost expenditure are also used as performance indicator:

$$\text{Time} = \textstyle\sum_{m \in M, e \in E:\text{dest €}=\gamma} \mathbf{E}\big(t_{ev} + t_{\gamma v}\big) z_{\text{evm}} \tag{3}$$

$$\text{Cost} = \textstyle\sum_{\gamma \in \Gamma} \mathbf{E}(c^c + c^d) x_\gamma \tag{4}$$

Other performance indicators and metrics can also be included explicitly in the optimisation problem (e.g. maximum flow, risk).

Several constraints are then included. Each mission is indeed completed by only one path. Extreme nodes in the path are connected only to a single edge. Intermediate points have a balance of in-link and out-link. These constraints are mathematically expressed in the following equation

$$\sum_{\substack{e \in E \\ \text{dest }(e)=\gamma, v \in V}} z_{evm} - \sum_{\substack{e \in E \\ \text{source(e) }=\gamma \\ v \in V}} z_{evm} = \begin{cases} -1, & \text{if } u^1_{\gamma m} = 1 \\ 1, & \text{if } u^2_{\gamma m} = 1 \forall m \in M, \gamma \in \Gamma \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Additionally, each mission has only one starting and one termination station that needs to be a storage infrastructure. Further constraints define the domain of the optimisation variables. An example of optimal network design is shown in Fig. 5. The figure in the left shows a graph representation of the drone delivery network. It is a multi-layer graph where each layer (colour) represents possible connections between stations for a particular drone type. Nodes indicate physical stations and their colour clusters them between source, receiver and source-receiver stations. The figure on the right side shows instead the optimal network solution optimised for resilience. Points still represents the network stations, but here the colours define them as airports, NHS infrastructures and additional stations chosen by the optimiser. Links between nodes represent feasible connections between stations. Again, different colours refer to different drone types: red lines are possible flight connections for the small drones provided by Skyports while black lines refer to the big Black Swan drones from Dronamics.

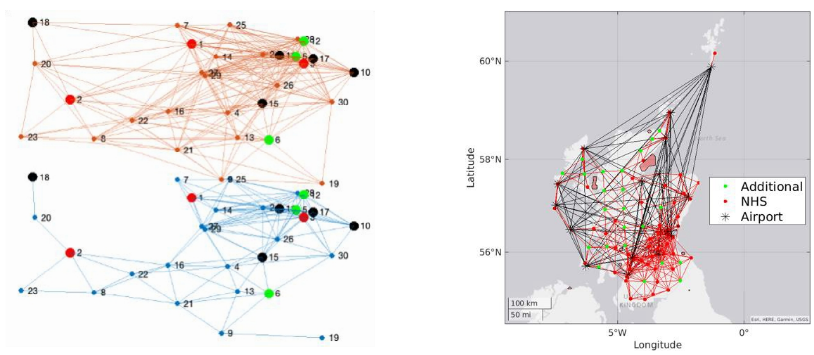


Fig. 5. Drone delivery network in Scotland: (a), Multi-level representation of the drone-based delivery network. Each layer represents feasible connections between stations with a specific drone type: drone type 1 (blue) and type 2 (red) (b) solution optimised for resilience. Here two commercial drones have been considered: Skyport (red) and Dronamics (black).

3.2 Defibrillator emergency delivery network

The problem aims at identify the number and location of drone stations required to allow drones to delivery portable defibrillators in case of emergency. In this example the NHS board of Grampian in Scotland has been considered. Historical data of cardiac arrest for the board has been used to produce the position and of emergency cases. A critical threshold of 8 minutes has been used for the drone to reach the emergency location (if the defibrillator is not used in this time windows the chance that a patient will survive are very low). This threshold is also a target for ambulance service and as in Fig. 6(a) , we can notice that the ambulance coverage in 8 minutes is limited. From Fig. 6(a) we also notice that many of historical emergency cases are outside the theoretical ambulance coverage area assuming that there are not traffic restrictions. For solving the Facility Location Problem to identify locations of drone storage stations (with available drones), a bi-objective formulation can be defined as in the following:

$$\min_{n>0,x,y}\left[n, -\Phi\left(\min_i\left(t_{i,e}\right) \le \nu\right)\right]^T \forall i \in I, e \in E \qquad (6)$$

For a given threshold in probability, the previous formulation can be reduced to:

$$\begin{aligned} &\min_{n>0,x,y} \\ \text{s.t.}\quad &\Phi\left(\min_i\left(t_{i,e}\right) \le \nu\right) \ge 0.9, \forall i \in I, e \in E \end{aligned} \qquad (7)$$

This way, we can cover more cardiac arrest cases by sending defibrillator by drones with a coverage of 90% of the cases using 17 drone stations as shown n Fig. 6(b).

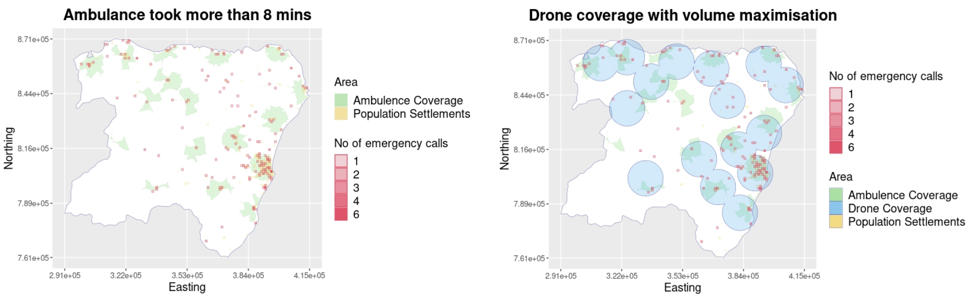


Fig. 6. Results for the sub-problem of Network Design. (a) Grampian cardiac history of arrest density (b) Drone stations in NS Grampian.

3.3 Network planning / scheduling

The network planning and scheduling refers to the calculation of the optimal set of delivery plans for each mission defined as the couple of locations for Pickup and Delivery. Missions depend on both predefined orders or new emergency ones. Planning and scheduling means selecting a drone for each mission and defining the routes for each drone. The problem includes the vehicle routing problem (VRP) with an heterogeneous fleet of drones, pick-up and delivery, payload capacity, time windows constraint, and multiple drone ports. Similar to the notion of a standard VRP, a drone graph is represented as G(V,L) with V set of vertices, L set of links. Here each vertex is associated with certain facilities such as: charging, storing, taking-off and landing. A fleet of drones are distributed across these vertices and they move from one vertex to another via the links to complete the orders. To complete these deliveries we have a total of n different drones of τ different types.

A robust scheduling required the maximisation of the network reliability while minimasing individual delivery times, as well as the risk of ground impact. To account for the unavoidable uncertainty, expectation of the objective functions are used. The routing and scheduling problem can be expressed in the following way:

$$\begin{aligned} \min \quad & \max_{1\le i\le n_d} \mathbb{E}[t_i^A(\tau,\cdot)] \\ \min \quad & 1-\mathbb{E}(\mathrm{Rel}(\cdot)) \\ \min \quad & \mathbb{E}(\mathrm{Risk}(\cdot)) \end{aligned} \qquad (8)$$

such that

$$
\begin{aligned}
\max_{1 \le i \le n_d} \mathbb{E}[t_i^A(\tau,\cdot) - t_i^R(\cdot)] &\le 0 \\
\mathbb{E}[SoC(\cdot)] &\ge \nu_{\text{soc}} \\
\underline{\nu}_T \le \mathbb{E}[T_{\text{pack}}(\cdot)] &\le \bar{\nu}_T
\end{aligned}
\tag{9}
$$

where ν_{soc} is the tolerance associated with the discharging of the drone batteries $\underline{\nu}_T$, $\bar{\nu}_T$ are the lower and upper bound of the temperatures within which a package remains unaffected, n_d $\Longrightarrow$ the number of delivery missions, $t_i^A(\cdot)$ $\Longrightarrow$ the time taken by a drone for the i-th mission, Rel$(\cdot)$ $\Longrightarrow$ the system reliability, Risk$(\cdot)$ $\Longrightarrow$ the risk associated with ground impact of drone crash, $t_i^R(\cdot)$ $\Longrightarrow$ the time taken by a car for the i-th mission, SoC$(\cdot)$ $\Longrightarrow$ the charging status of a drone, $t_{pack}(\cdot)$ $\Longrightarrow$ the temperature of the package(s) transported by a drone.

In general, these quantities have a complicated functional expression occurring from dynamical process. Therefore, it is rather expensive to evaluate each of these expressions individually for our analyses. To overcome this issue, we consider surrogate methods to construct Low Fidelity Models and perform the optimisation for Vehicle Routing Problem.

3.4 Individual path planning

A further optimisation problem included in SHEPHERD is the Path Planning. This is not an independent problem since it is coupled with the two previously presented and can be considered as a lower optimisation layer for them. Given a point to point flight connection, we aim to define the optimal path that connect them and optimise a set of pre-defined metrics. Fig. 7 shows the results for a bi-objective optimisation problem where the objectives are length and risk of ground impact. Figure (a) in the left shows the start and end point for the path planning problem. The map includes also the population density distribution and the area has been discretised in a fine grid where for each point it is known its location and population value. Multiple optimal path solutions are plotted with different colours on top of the map. They are optimal from a multi-objective Pareto point of view. Their trade-off is shown in the figure (b) in the right.

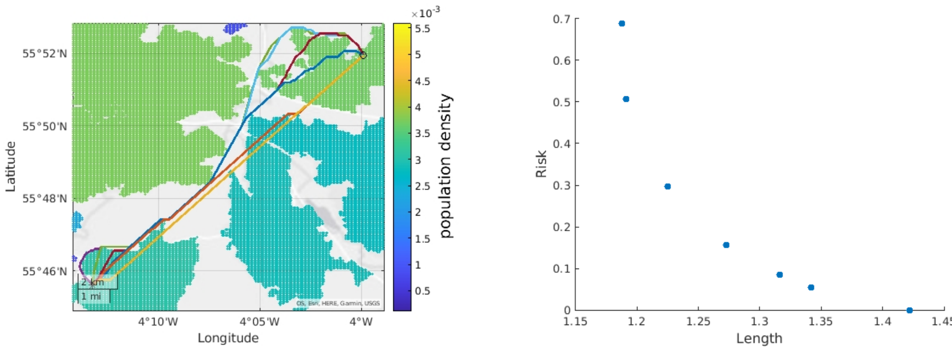


Fig. 7. Results for the Path Planning problem. (a) Map, population density distribution and path planning alternatives with respect to risk and time. (b) Bi-objective Pareto trade-off between solutions.

4 Conclusions

A high level overview of the aspiration and capability of the SHEPHERD project has been presented. The developed tools allow the strategic design and robust operation of a drone-based delivery network. The tools has multiple fidelities capabilities that can be used interchangeably within a modular framework. Models include the environment, sub-systems, systems and the system-of-systems. A set of tools also have been included for a robust optimisation and reliable decision making at different scales in time and space.

In summary, SHEPHERD can support the realisation of the first drone-based delivery network of medical items in Scotland.

Acknowledgements

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References

Amukele, T. K., et al. 2016. Drone transport of microbes in blood and sputum laboratory specimens. Journal of Clinical Microbiology 54, 2622–2625. doi: 10.1128/JCM.01204-16.

Basu, T., et al. 2023. Drone Flight Time Estimation Under Epistemic Uncertainty. In European Conference on Safety and Reliability (ESREL 2023) Doi:10.3850/978-981-18-8071-1_P738-cd

Project CAELUS, 2022. Care & Equity – Healthcare Logistics UAS Scotland, https://www.agsairports.co.uk/drones, Retrieved on 1/05/2024.

Filippi, G., et al. 2022. Resilience Optimisation for Next Generation Drone Logistic Networks. In European Conference on Safety and Reliability (ESREL 2022). Doi: 10.3850/978-981-18-5183-4_S13-02-486-cd

Filippi, G., et al. 2023. A Digital Twin Model for Drone Based Distributed Healthcare Network. In European Conference on Safety and Reliability (ESREL 2023). Doi:10.3850/978-981-18-8071-1_P738-cd

Gao, C., et al. 2019. Does being multi-headed make you better at solving problems? a sur- vey of physarum-based models and computations. Physics of Life Reviews 29, 1–26. doi:10.1016/j.plrev.2018.05.002.

Gryte, K. et al., 2018. Aerodynamic modeling of the Skywalker X8 Fixed-Wing Unmanned Aerial Vehicle, 2018 International Conference on Unmanned Aircraft Systems (ICUAS), Dallas, TX, USA, 2018, pp. 826-835, DOI: 10.1109/ICUAS.2018.8453370

Jiang, C., Blom, H. A., Sharpanskykh, A. Third Party Risk Indicators and Their Use in Safety Regulations for UAS Operations. Doi:10.2514/6.2020-2901.

Li, G., Liu, Z., Hu, J., Li, H.-J. 2020. Leonardo, Telespazio and Bambino Gesu' children's hospital test the use of drones for biomedical material delivery. https://www.leonardo.com/en/press-release-detail/-/detail/22-10-2020- leonardo-telespazio-and-bambino-ges%25C3%25B9-children-s-hospital-test-the-use-of-drones-for-sanitary-material-delivery Retrieved on 01/05/2024

Lippi G. and Mattiuzzi, C. 2016.Biological samples transportation by drones: ready for prime time? Ann Transl Med. Mar; 4(5): 92. doi: 10.21037/atm.2016.02.03Metternet. Matternet launches drone delivery operations at labor berlin in germany. https://www.prnewswire.com/news-releases/matternet-launches-drone-delivery-operations-at-labor-berlin-in-germany-301175019.html Retrieved on 01/05/2024.

Metoffice. 2024. Met Office Weather DataHub. https://www.metoffice.gov.uk/services/data/met-office-weather-datahub, Retrieved on 01/05/2024.

POST, 2018. S. Swiss post begins transporting laboratory samples for insel gruppe, https://www.post.ch/en/about-us/innovation/innovations-in-development/drones Retrieved: 01/05/2024.

Quintanilla, G. I., et al. 2021. A quickly deployed and uas-based logistics network for delivery of critical medical goods during healthcare system stress periods: A real use case in Valencia (Spain). Drones 5, 1. Doi:10.3390/drones5010013.