Resilient Network Design for Health Care System

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Abstract. Distributed health care network has been a key area of interest in improving the health care systems and with the recent developments of cost-effective unmanned autonomous vehicles (UAV), the use of drone for health care system is also gaining interest from different government organisations. Moving towards this direction, NHS (National Health Service) Scotland is also looking into the prospects of using drones for medical deliveries across Scotland for which we are interested in designing an optimal drone network. In general, to design such networks, we need to consider different quantities of interest such as flight time, capital expenditure, risk impact, etc.

In this contribution, we are specifically interested in discussing the resilience of a drone logistic network which is important to ensure an interrupted chain of communication within and between different regional boards of NHS Scotland as well as smooth delivery of life saving medical objects. We treat the drone network as a graph and see how the graph behaves when failures happen due to uncertain events. We associate a probability interval to each basic event and compute the corresponding network efficiency (ϵ_i) after its verification. We calculate this efficiency as a combination of all the pairwise 'reachability' within a pair of source and receiver locations within the network, given the state of the network. Network efficiency is a function of the expected time required by drones through optimal paths. We consider finally the possibility for nodes to recover after failure. This allows to quantify the reaction capability of the network after uncertain events. In this sense, resilience is the network ability to absorb shocks and recover after them.

We then use this to illustrate our result for different scenarios to explain the use of our proposed resilience metric and also give a notion of 'trade-off' between the cost of network design and the network resilience to assist the decision makers.

Keywords: delivery network, NHS, drones, resilience

1. Introduction

A promising direction to improve medical delivery system is given by technological shift to autonomous drones for distributed healthcare networks. Many flight trials performed all around the world have proved that this is a good direction. For example, (Amukele and Street, 2016) studied the transport of microbiological specimens including blood cultures by drone. Successful flight tests for medical delivery have been conducted in Spain (García and Vélez, 2021). Additional study on the impact of drone transportation on biological samples was explored in (Daalen and Holleman, 2021), revealing no adverse effects for turnaround times of less than 4 hours. Feasibility of drone logistic networks for delivering medical goods was observed by Leonardo and Telespazio (Daalen and Holleman, 2020) near Rome and by Matternet (Matternet, 2020) in Berlin. Similar initiatives were undertaken in Switzerland with Swiss Post, involving the transportation of laboratory samples between two hospitals (Swiss Post, 2018).

The UK government is investigating the potential for an autonomous Drone Logistic Network to aid in delivering medical supplies and support to remote regions. Indeed, the scattered population and geographical limitations of Scotland present challenges in providing equal access to crucial health services. In line with these efforts, the project 'CAELUS' (Care & Equity – Healthcare Logistics UAS Scotland) has been approved by the UK Industrial Strategy Future Flight Challenge Fund (CAELUS, 2024).

To achieve the objectives of CAELUS, we are creating SHEPHERD to analyse the impact of a drone logistics network within the context of Scotland. SHEPHERD integrates Digital Twin models of the complex networked system with optimisation and uncertainty quantification tools. This approach serves two purposes: designing the drone delivery network (strategic use) and ensuring its optimal operation (tactical use). The strategic use of SHEPHERD entails designing the entire Drone Logistic Network, optimised according to key performance indicators set by stakeholders. This design process occurs before constructing the physical network and is conducted entirely through virtual environment simulations. The design challenge is approached as a multi-objective generative network optimisation (Gao and Liu, 2019), taking into account factors like capital and operational costs, delivery time, network reliability, and resilience to unforeseen events. The tactical aspect of SHEPHERD addresses the network's operational challenges. This involves the online simulation of the Digital Twin during the actual use of the physical Drone Logistic Network to achieve optimal planning and scheduling. SHEPHERD also simulates various flight scenarios under uncertain conditions to determine the best course of action. This paper builds on the work proposed by the authors in (Filippi and Vasile, 2022; Basu and Filippi, 2023; Filippi and Basu, 2023).

This paper focuses on the strategical part of SHEPHERD. While more details about the algorithmic procedure for the optimisation can be found in (Filippi and Vasile, 2022), it is here given the definition of the Drone Logistic Network, of the network design optimisation problem and the main focus is on the network resilience metric.

2. Delivery Network Formulation

This section gives the mathematical formulation of the drone-based logistic network for the delivery of medical items and service in Scotland. The network is a complex system formed of stations and unmanned vehicles (UAV) where the UAVs fly to accomplish the delivery missions. Stations are defined at specific locations and have attached different combination of infrastructures. They also have different functionalities: indeed, the network includes Hospitals, Laboratories, GPs and Airports. Each one of these can be classified as source, receiver or source/receiver based on the flow of medical packages. The NHS system in Scotland is organised in 14 boards as shown in Fig. 1. They have substantial autonomy even if there is national interdependence between them. The drone-based delivery network is then modelled as a two level grid where the lower (local) refers to the boards and the higher (global) to the national level.

From the mathematical point of view, a set K is used to represent all the existing stations (Hospitals, Laboratories, GPs and Airports) with $k_j \in K$ for $j = 1, .., n_k$. Additional stations (not currently built) can be further considered to improve the network, with reference to a generic metric, and they are defined in the set I with $i_j \in I$ for $j = 1, ..., n_i$. The optimal definition of additional locations, chosen within I, is important to guarantee the connectivity of the network and to improve its performance and functionalities. The whole set of locations in the delivery network is represented by Γ, such that $\Gamma = K \cup I$ with $\gamma_j \in \Gamma$ for $j = 1, ..., n_\gamma$ where $n_\gamma = n_k + n_i$.

A number of infrastructures can also be added to each location $\gamma_j \in \Gamma$. Two types are here considered: charging infrastructures $s_{ch} \in S^{ch}$ and drone storage infrastructures $s_{st} \in S_{st}$. The former are required do to the limited battery capacity of drones. Three alternative activities can be performed for the given (selected) s_{st}. The drone can wait at the station during the whole charging process, the discharged battery can be swapped with a new battery pre-charged and stored at the same location, or the payload can be moved from the drone with a discharged battery to a new drone with a charged one parked at the same location.

We suppose then that the list of delivery missions M to be performed through the network is known. M is defined by the set of coupled pick-up and delivery station (P_m, D_m), with $P_m, D_m \in \Gamma$ $\forall m \in M$.

A set of different types of drones V is finally considered where each $v \in V$ has its own characteristic and performance.

The network can then be formalised as a multi-layer graph $G(\Gamma, E^v)$. Γ is the set of all nodes as defined above where $\forall \gamma \in \Gamma$, a combination of infrastructures is defined: $s_{sh,\gamma}$ and $s_{st,\gamma}$. E^v is the set of all edges that are feasible with drone type v:

$$E^v = \{(\gamma_i, \gamma_j) \mid \gamma_i, \gamma_j \in \Gamma, d(\gamma_i, \gamma_j) \leq R^v\}. \tag{1}$$

Fig. 1 (a) is an example of a network with two types of drones that are modelled with a blue layer and a red layer.

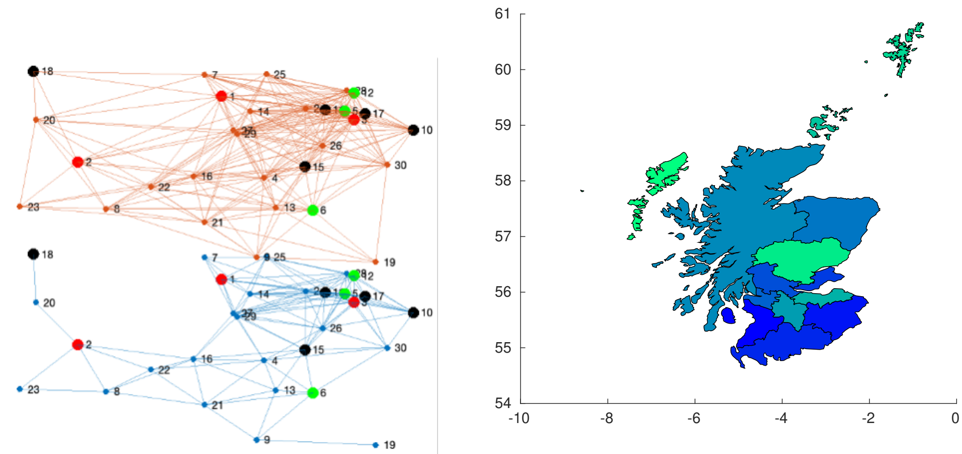

Figure 1. left: the delivery network is modelled as a multi-layer graph where each layer represents connections due to a specific drone type. *right:* map of the 14 NHS boards.

3. Network Optimisation Problem Formulation

The optimisation problem considered in this paper is the network design optimisation which includes three main optimisation sub-problems. The first is the facility location problem which goal is to select a sub-set of locations from a large list of possible alternatives. From the network definition given above, this choice applies to the elements inside $I \subset \Gamma$. The second considered optimisation problem is the resource allocation problem that associates to each selected location $\gamma \in \Gamma$, the optimal combination of infrastructures $s_{sh,\gamma}$ and $s_{st,\gamma}$. Last, a vehicle routing problem is considered which defines the optimal route between each couple of source-receiver and select the optimal drone type to use. A vector of decision variables $\mathbf{d}$ is defined that captures the design choices of the previous problems:

$$\mathbf{d} = \left[x_{i_1}, ..., x_{i_{n_i}}, s_{ch,1}, ..., s_{ch,n_\gamma}, s_{st,1}, ..., s_{st,n_\gamma}, p_1, ..., p_m\right] \tag{2}$$

where the first part of the vector, $[x_{i_1}, ..., x_{i_{n_i}}]$, defines which additional locations are included in the network, the second part, $[s_{ch,1}, ..., s_{ch,n_\gamma}, s_{st,n_\gamma}, s_{st,1}]$ attaches charging and storing infrastructures respectively to existing nodes and selected new locations and the last part $[p_1, ..., p_m]$ defines the nominal route plan for each mission $m \in M$.

A bi-level procedure has been implemented for the solution of the network design optimisation. A local network is designed for each NHS board in Fig. 1 (b) and a global overarching national grid is also optimised for the whole Scotland.

The network design is a multi-objective optimisation problem for which multiple performance metrics can be considered: capital and operational cost, network reliability, network resilience, time for delivering, etc. This paper focuses on the overall time for delivery, the network capital cost and the network global resilience:

$$\mathbf{f}(\mathbf{d}, \mathbf{u}) = [\mathrm{Time}(\mathbf{d}, \mathbf{u}), \mathrm{Cost}(\mathbf{d}, \mathbf{u}), \mathrm{Resilience}(\mathbf{d}, \mathbf{u})]^T. \tag{3}$$

where $\mathbf{d}$ is defined above and $\mathbf{u}$ include the system and environmental uncertainties.

In particular, this section defines the first two metrics, Delivery Time and Network Capital Expenditures, while network resilience is presented more in detail in the next section.

The delivery time is calculated as the sum of all the required times for all the deliveries in M. It is here considered the expected time for connecting all couples of nodes within the routes and for the operations at the ground stations:

$$\mathrm{Time} = \sum_{\substack{m \in M, \\ e \in E : \mathrm{dest(e)} = \gamma}} \mathbb{E}(t_{ev} + t_{\gamma v}) z_{evm}. \tag{4}$$

In Eq. (4), t_{ev} is the time for link e with drone type v, $t_{\gamma v}$ is the ground operation time at node γ and z_{evm} is an indicator variable that is 1 if link e is used to connect P_m and D_m with drone type v for mission $m \in M$, 0 otherwise.

The capital cost of the delivery network is calculated instead as the sum

$$\mathrm{Cost} = \sum_{\gamma \in \Gamma} \mathbb{E}\big(c(s_{0,\gamma}) + c(s_{ch,\gamma}) + c(s_{st,\gamma})\big) x_\gamma \tag{5}$$

where $c(s_{0,\gamma})$ quantifies basic infrastructural expenditures, while $c(s_{ch,\gamma})$ and $c(s_{st,\gamma})$ quantify the capital costs for charging and storage infrastructure respectively. The parameter x_γ is finally an indicator variable which value is 1 if node γ is included in the solution, 0 otherwise.

4. Network Resilience

The resilience of a complex system is a property related to the dynamical capability to react and adapt to external and/or internal unpredicted events in order to maintain its functionality. This definition implies the ability to absorb shocks due to uncertain events, minimising the lost of performance, and to recover partially or entirely to the previous nominal conditions.

Consider a generic network configuration defined by a set of stations, infrastructures attached to the stations and an heterogeneous fleet of available drones. The information about this network configuration is condensed in the vector of design decision variables $\mathbf{d} \in D$ as in Eq. (2) and in the vector of uncertain variables $\mathbf{u} \in U$.

The network resilience proposed in this paper is the calculated as the expected value of an operator Φ:

$$\text{Resilience} = \mathbb{E}\Big(\Phi_e(\mathbf{d}, \mathbf{u}_e)\Big) = \sum_{e \in E} p_e \Phi_e(\mathbf{d}, \mathbf{u}_e) \tag{6}$$

where p_e is the the probability of the event $e \in E$ and the operator Φ_e models the network dynamics under the uncertain event e. Following Eq. (6) there are two objects that have to be defined: the probability space and the operator Φ.

4.1. Probability space

We consider a set of independent events e_i that includes the functional state of each node in the network (totally functioning or totally failed) and the flight range variation of each drone type due to weather conditions. To cope with imprecision and lack of knowledge about the frequency of these events, we assume that the probability of them to happen is elicited from expert opinion, giving rise to probability bounds $p_{e_i} = [\underline{p}_{e_i} \bar{p}_{e_i}]^T$ for each event $e_i \in E_i$.

Since we assume the elementary events to be mutually independent and the probabilities of the elementary events e_i to be in the interval $[0, 1]$, the probability space of events $e \in E$ is given by the Cartesian product of the elementary p-boxes:

$$p_e = \Big[\prod_i \underline{p}_{e_i}, \prod_i \bar{p}_{e_i}\Big]^T. \tag{7}$$

4.2. Network dynamics

The second element in Eq. (6) is the operator Φ_e which quantify the ability of the network to minimise the lost of performance due to the uncertain event, and to recover partially or fully after it. The operator Φ is related to the network efficiency ϵ which models degradation and recovery under uncertain external/internal events as function of time for delivery.

In nominal condition, the delivery time of mission m between source (pick-up) node P_m and sink (delivery) node D_m is:

$$T^m_{nom} = \min_{\mathbf{p}} \Big[\mathbb{E}\Big(\mathrm{Time}^m_{\mathrm{nom}}(G, \mathbf{p}, \mathbf{u})\Big)\Big], \qquad \forall m \in M \tag{8}$$

where $\mathbf{p}$ is the part of the decision vector $\mathbf{d}$ in Eq. (2) that refers to the route plan definition. The nominal performance indicator, the nominal network efficiency, is the constant function over time:

$$\epsilon_{nom}(t) = \sum_{m=1}^{M} \frac{1}{T^m_{nom}}. \tag{9}$$

The realisation of a generic event $e \in E$ modifies the topology of the network by deactivating one or more stations and/or reduces the nominal distance a drone can fly. After event e then, the delivery time of mission m between source node P_m and sink node D_m becomes:

$$T^m_e(t) = \min_{\mathbf{p}} \Big[\mathbb{E}\Big(\mathrm{Time}^m_{e,t}(G, \mathbf{p}, \mathbf{u})\Big)\Big] \tag{10}$$

In Eq. (10) it is considered the possibility for failed nodes in the network to recover as consequence of targeted maintenance. In particular, a policy is included in the model for the decision of the sequence of nodes to re-activate. If the event $e \in E$ includes the failure of multiple (more than one) nodes, the next repaired node is given by the solution of:

$$\text{next node} = \arg\ \max_{i \in I_f} \epsilon^i_e \Delta T^i \tag{11}$$

where ϵ^i_e is the efficiency of the network after event $e \in E$ with recovery i and $\Delta T = T_{max} - T_{rep,i}$ is the time window between the moment the node i is repaired and the upper bound of time considered.

Similarly to the nominal case, the network efficiency after event e is:

$$\epsilon_e(t) = \sum_{m=1}^{M} \frac{1}{T^m_e(t)}. \tag{12}$$

In this case, due to the repairing policy, $\epsilon_e(t)$ is a monotonic function increasing over time.

The network efficiency in Eq. (12) is then normalised based on the nominal condition:

$$\hat{\epsilon}_e(t) = 1 - \frac{\epsilon_{nom} - \epsilon_e(t)}{\epsilon_{nom}} \tag{13}$$

Fig. 2(a) shows an example of the efficiency function for both the nominal case an a generic event $e \in E$. Nominal network efficiency is time-independent and is represented by the blue rectangle. The red area, on top of the blue one, instead represents the dynamics of the network after shock absorption and recovery due to nodes repairing.

Finally, the operator Φ_e for event e in Eq. (6) is calculated as the integral of the normalised efficiency $\hat{\epsilon}_e(t)$, that corresponds to the red area in Fig. 2(a):

$$\Phi_e = \int_{t_0}^{t_\infty} \hat{\epsilon}_e(t; \mathbf{d}, \mathbf{u}) \tag{14}$$

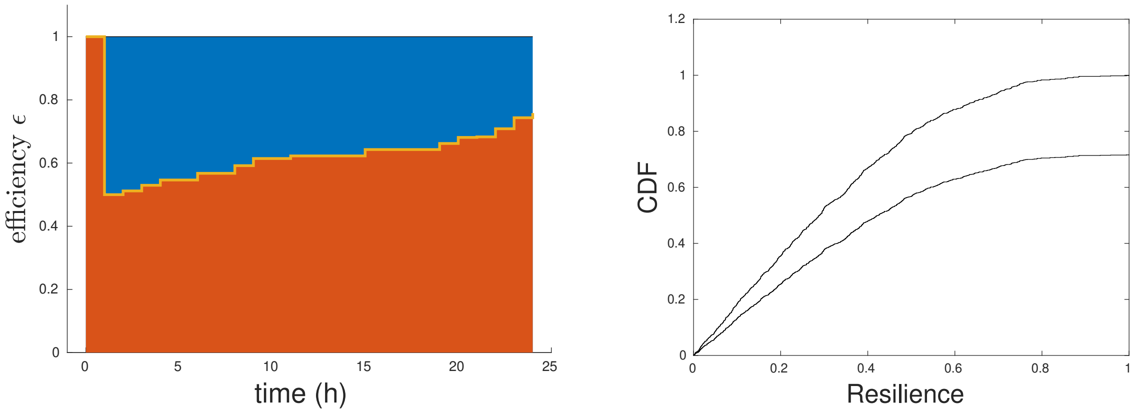

Figure 2. Example of network resilience in a synthetic test case. *left*: shock absorption and recovery. *right*: lower and upper probability for the resilience.

The combination of the p-boxes in Sec 4.1 and the operator Φ in Sec 4.2 allows to build the lower and upper bound of the resilience probability distribution as in Fig. 2(b) and to quantify the network resilience as in Eq. (6). Fig. 2(b) shows an example of the propagated lower and upper probabilities for the given definition of resilience.

5. Test case

The network design optimisation problem defined above is finally applied for the definition of a optimal set of delivery networks for NHS Scotland. Following the bi-level formulation, two levels of granularity for the network have been considered. The lower level is used to define the local delivery networks for each of the 14 NHS Scottish Boards: Ayrshire and Arran, Borders, Dumfries and Galloway, Fife, Forth Valley, Greater Glasgow and Clyde, Grampian, Highland, Lanarkshire, Lothian, Orkney, Shetland, Tayside, Western Isles. Then the upper level is used for the overarching National network in the whole Scotland.

Two types of drones are considered: a small electric quad-rotor produced by Skyports and a big, fixed wing fuel-based drone produced by Dronamics. The latter type of drone is faster and has higher package and distance capacity, but is allowed to fly only between airports location.

For each board, an hub-and-spoke model has been used to simulate the continuous flow of delivery packages from central hubs to distributes spokes. I particular, two hubs have been included: the main hospital and the main airport in the board. The airports are considered as a gates to all other boards through the use of Dronamics drone.

A single-objective problem is solved, in order to find a feasible network for each NHS board and for the national grid that is optimal for Time metric. Given the generative nature of the optimisation algorithm, a number of sub-optimal networks are also calculated and stored in an archive.

The archives of solutions are finally used to generate optimal Pareto fronts with respect to Cost and Resilience metrics.

6. Results

A network optimisation has been performed for each NHS board considering as objective function the time for delivery. As an example, consider first the Western Isles board. Fig. 3(a) shows the list of all the considered locations: 'NHS' and 'Airports' locations (set K) and 'Additional' locations (set I). The solution of the optimisation problem is represented by the network design in Fig. 3(b): the network has been designed in order to guarantee optimal deliveries between each source/receiver (red points) and the receivers (blue points). The solution considers the use of both types of drones, red lines for small quadrotor and black lines for big fixed-wing. The choice between them depends on both the expected time of flight and ground operations and also on the drone constraints.

The archive of simulated network solutions is then used to reconstruct the optimal Pareto Set based on the trade-off between 'Capital Cost' and 'Resilience'. In particular, Fig. 3(c) shows the optimal network for cost while Fig. 3(d) the one optimal for resilience.

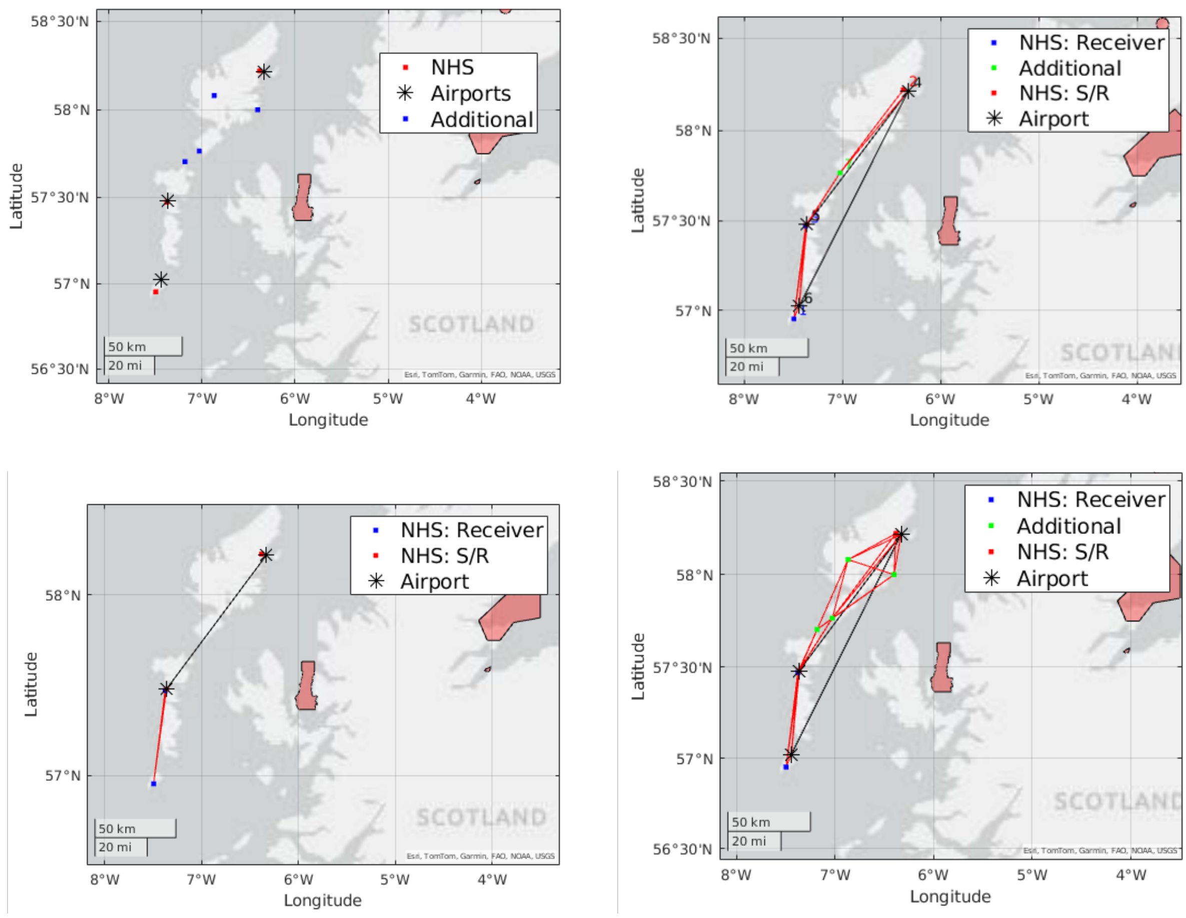

Figure 3. Maps for the Western Isles Board. *top left:* initial grid for the Western Isles Board. *top right:* . *bottom left:* . *bottom right:* .

This trade-off is better represented in Fig. 4. In particular, Fig. 4(a) is a scatter plot of all the network solutions in the optimal set. Fig. 4(b) instead compares the two extreme solutions corresponding to Fig. 3(c,d) respectively. It shows the p-boxes of the CDF for the operator Φ introduced in Sec. 4.2. The dotted blue curves are the lower and upper bound of the probability for the minimum cost / minimum resilience solution while the continuous black lines are the lower and upper probabilities for the maximum resilience / maximum cost solution.

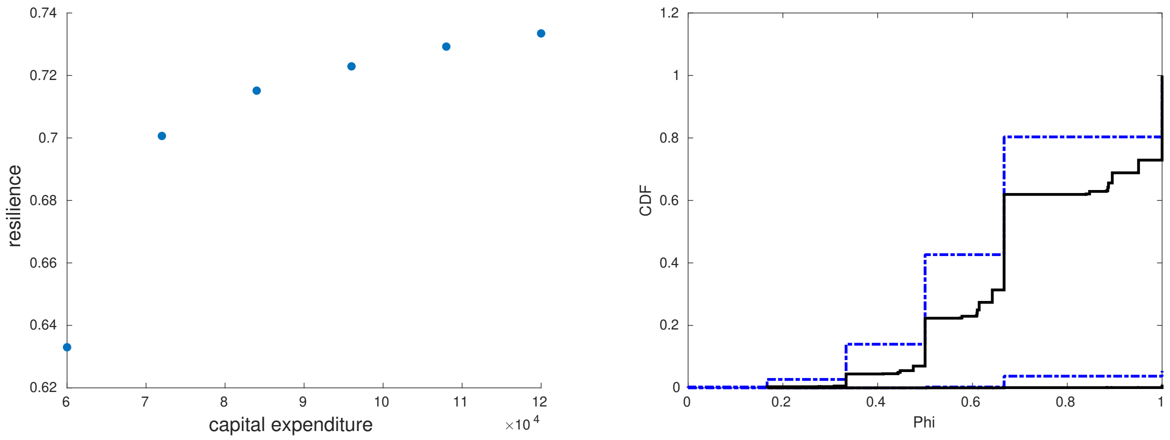

Figure 4. Pareto set solutions for the Western Isles Board. *left*: Pareto front between cost and resilience. *right*: lower and upper CDF for the probability distribution of the resilience; black curves correspond to the maximum resilience solution and blue ones to he minimum cost.

The procedure presented above has been finally repeated for all the NHS boards and for the national grid.

Figs. 5 and 6 shows the optimised networks using time as objective function. Fig. 5 refers to each NHS board while Fig. 6 depicts the overarching national grid. Similarly, Fig. 7 and Fig. 8 displays the optimised networks for cost. Fig. 9 and Fig. 10 display optimal network for the resilience metric.

7. Conclusion

The paper presents a portion of the ongoing contributions by the authors towards developing a digital blueprint for the first drone-based delivery network in Scotland for the NHS. It contextualises the project and outlines the benefits SHEPHERD could offer the NHS system.

It specifically delves into the network design challenge, with a particular emphasis on defining network resilience. It includes the modelling of lack of knowledge and imprecision in the definition of the probability boxes for the possible uncertain events and propagate this uncertainty thought the network model to understand the effect on the delivery system. In particular, the network, modelled as a multi-layer graph has the ability to react to uncertain shocks and lost of performance through the adaptation of the delivery planning and the recovery of failed nodes.

The methodology finally uses a bi-level framework across all NHS boards and the national grid as a whole.

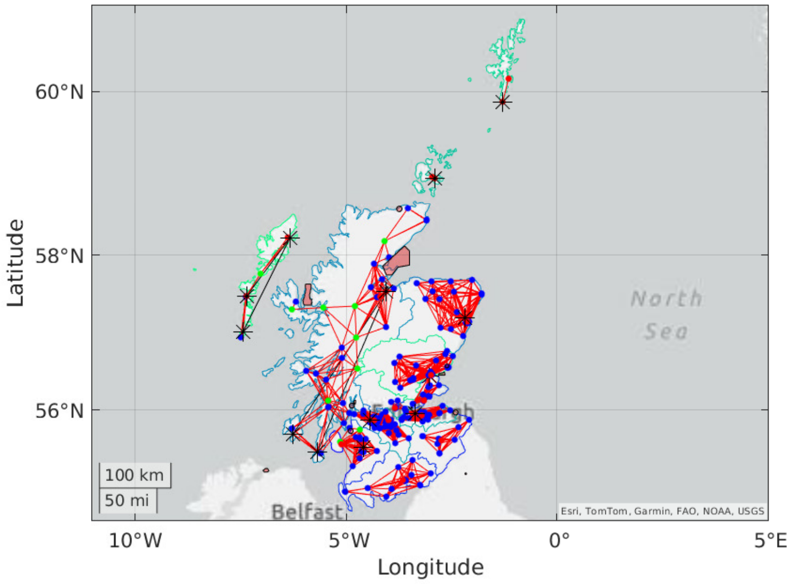

Figure 5. optimal network for each NHS board. The considered objective function is the delivery time

References

T. K. Amukele and J. Street and K. Carroll and H. Miller and S. X. Zhang. Drone Transport of Microbes in Blood and Sputum Laboratory Specimens. *Journal of Clinical Microbiology*, 54, 2622–2625, 2016.

Quintanilla García, Israel and Vera Vélez, Norberto and Alcaraz Martínez, Pablo and Vidal Ull, Jordi and Fernández Gallo, Beatriz. 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). , 54, 2622–2625, 2021.

F. V. Daalen, F. Holleman, C. Visser and S. E. Geerlings Optimizing the process of blood culture collection. *European Congress of Clinical Microbiology and Infectious Diseases (ECCMID)*, 2017.

Guijun Li and Zhidong Liu and Jun Hu and Hui-Jia Li Leonardo, Telespazio and Bambino Gesu' Children's Hospital test the use of drones for biomedical material delivery. , 2020.

Matternet Launches Drone Delivery Operations at Labor Berlin in Germany. , 2020.

We are project CAELUS. , 2024. https://www.agsairports.co.uk/drones

Chao Gao and Chen Liu and Daniel Schenz and Xuelong Li and Zili Zhang and Marko Jusup and Zhen Wang and Madeleine Beekman and Toshiyuki Nakagaki Does being multi-headed make you better at solving problems? A survey of Physarum-based models and computations. *Physics of Life Reviews*, 2019.

Swiss Post begins transporting laboratory samples for Insel Gruppe. , 2018. https://www.post.ch/en/about-us/media/press-releases/2018/swiss-post-begins-transporting-laboratory-samples-for-insel-gruppe#:~:text=In%20the%20pilot%20project%20in,Jocham%2C%20Insel%20Gruppe's%20CEO.

Filippi, Gianluca and Vasile, Massimiliano and Patelli, Edoardo and Fossati, Marco Resilience Optimisation for Next Generation Drone Logistic Networks. *European Conference on Safety and Reliability (ESREL)*, 2022.

Basu Tathagta, Filippi Gianluca, Vasile Massimiliano, Patelli Edoardo and Fossati Marco Drone Flight Time Estimation Under Epistemic Uncertainty. *European Conference on Safety and Reliability (ESREL)*, 2023.

Filippi Gianluca, Basu Tathagta, Vasile Massimiliano, Patelli Edoardo and Fossati Marco A Digital Twin Model for Drone Based Distributed Healthcare Network. *European Conference on Safety and Reliability (ESREL)*, 2023.

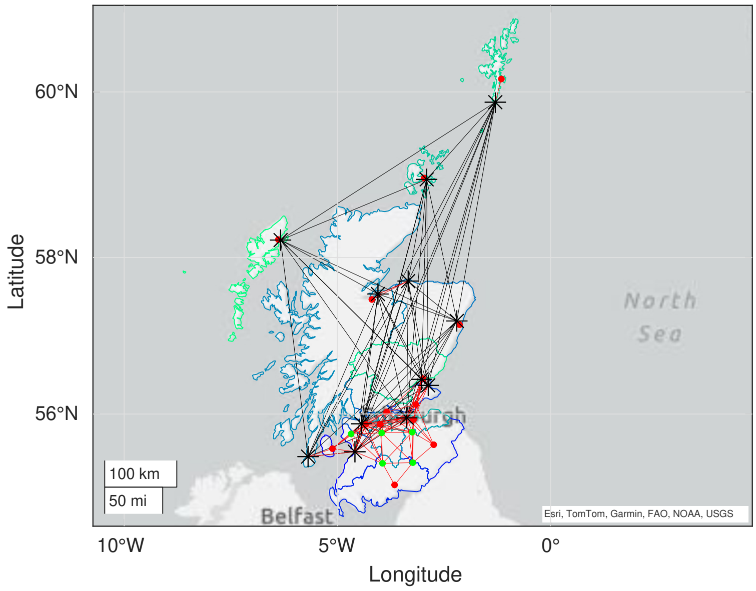

Figure 6. optimal intra-layer network over the different NHS boards. The considered objective function is the delivery time

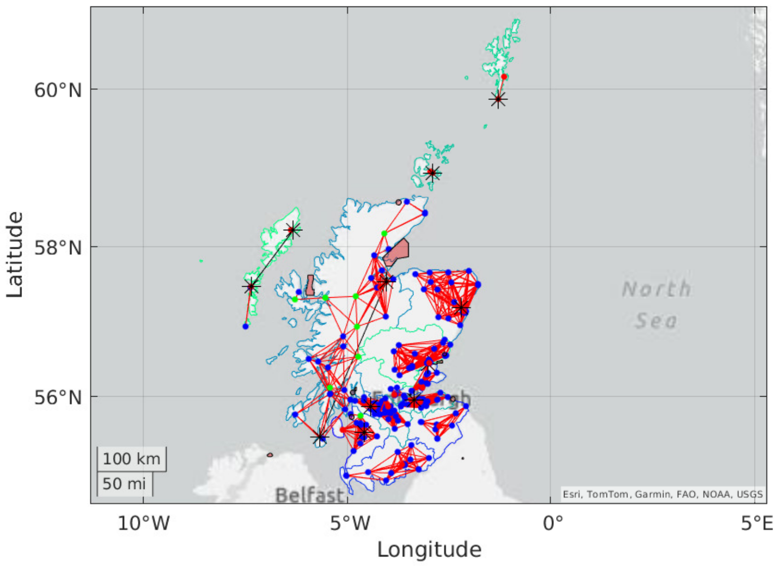

Figure 7. optimal network for each NHS board. The considered objective function is the capital expenditure

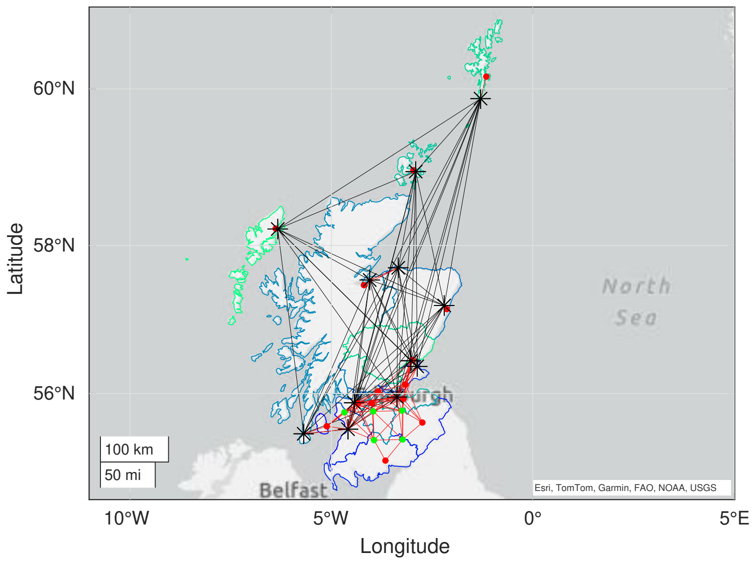

Figure 8. optimal intra-layer network over the different NHS boards. The considered objective function is the capital expenditure

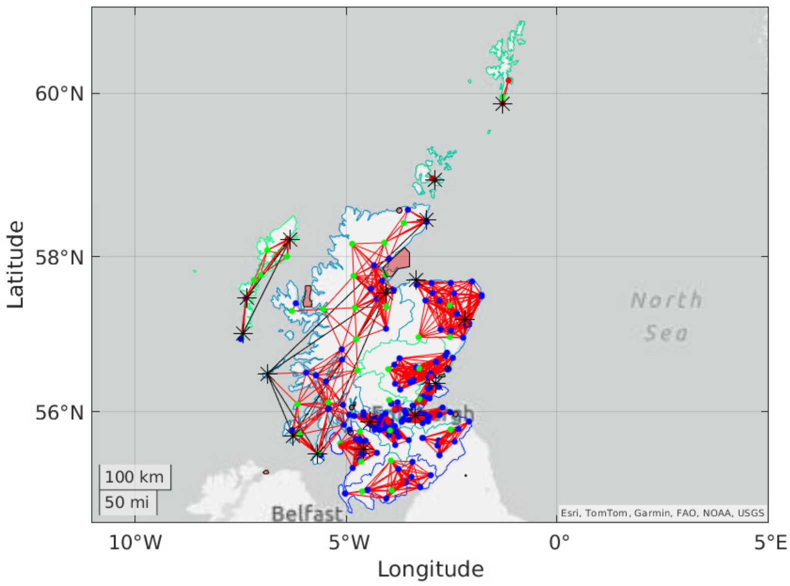

Figure 9. optimal network for each NHS board. The considered objective function is the network resilience

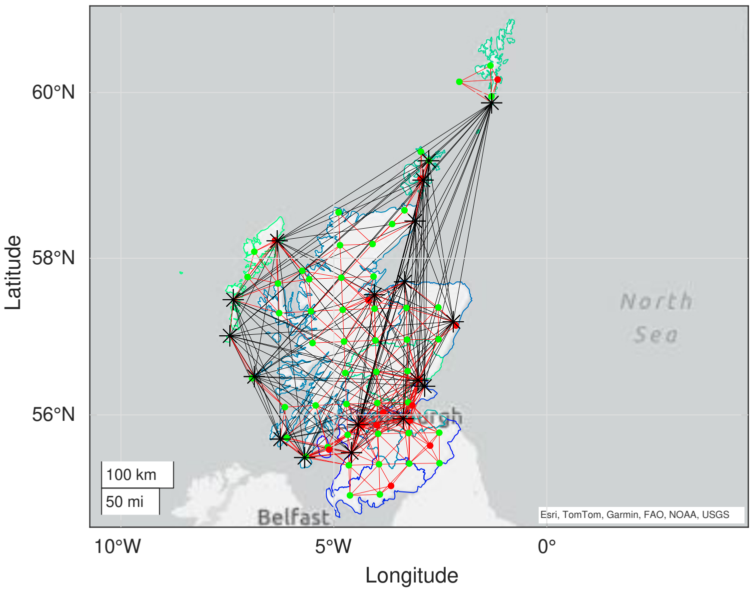

Figure 10. optimal intra-layer network over the different NHS boards. The considered objective function is the network resilience