The 9th International Symposium on Reliability Engineering and Risk Management (ISRERM 2024)
October 18-21, 2024, Hefei, China

Drone Assisted Emergency Response Model for Scotland

T. Basu*[1], G. Filippi[2], B. Parsonage[2], E. Patelli[1], M. Vasile[2], and M. Fossati[2]

[1] *Civil and Environmental Engineering, University of Strathclyde, Glasgow G1 1XQ, UK*
[2] *Mechanical and Aerospace Engineering, University of Strathclyde, Glasgow G1 1XQ, UK*

Abstract

A drone-based network to assist health services has been an emerging topic in recent times. Many countries are already exploring the use of Drone based logistic network for medical goods delivery. Following this path, UK government is also exploring this idea through project CAELUS (Care & Equity – Healthcare Logistics UAS Scotland) consortium. A part of this service is to use drone logistic network for supplying Automated External Defibrillators (AEDs) to assist patients suffering from cardiac arrest. This is particularly important as even though it is mandatory to send an ambulance to a cardiac arrest call, it is not always possible to reach a patient in time because of certain external influences such as availability of an ambulance, traffic conditions. A drone network will therefore allow us to send an AED as early as possible to the patient so that they can be revived in most of the cases by the time an ambulance reaches. Having this in mind, we construct a facility location problem that aims to improve the resilience of the emergency response service provided by Scottish Ambulance Service (SAS). To do so, we tackle this problem as a time dependent problem, where we want to achieve a certain probabilistic threshold of drone coverage by allocating drone stations across different sub-regions of Scotland. This region-specific problem allows us to solve the optimisation problem with lesser computational term but also serves a very important aspect of the emergency response system, 'healthcare for all'. Any sort of statistical model relies on observational data and therefore we need to be very careful of the heterogeneity present in the data. Since, the number of recorded calls is very much dependent on the population of the area, having a global probabilistic model will only benefit the patients from the metro cities where most people reside. However, a region-based approach will ensure that we have drone stations in different parts of Scotland which will serve the patients from rural areas. Based on this approach we present a case study based on the region called 'Grampian' and show different metrics associated with our analysis such as percentage of land covered, percentage of population settlements covered and most importantly expected percentage of cardiac calls that we can cover. Moreover, we compare the case, where we only use the ambulance stations as drone port to observe the metrics we mention before. This is particularly interesting as constructing a drone station comes with additional cost both in the design and operation phase. So, using the ambulance station also reduce those cost, which might be beneficial in certain cases.

Keywords: Drone Logistic Network, Emergency Response Service, Resilience Engineering

1. Introduction

Drone assisted health service is an emerging topic and several countries have already tested [1–4] the use of drone for this purpose. Moving in this direction the UK government is also checking the possibility of a drone logistic framework through the project 'CAELUS'. The main focus of the project is to assist the National Health Service (NHS) of Scotland for smooth transportation of medical objects to remote areas of Scotland as well as completing quick deliveries in urban environments. Through this project, the consortium organised a successful flight trial from Glasgow airport to NHS Golden Jubilee Hospital [5].

Following the success of the flight trial, we are interested in its possible impact in assisting the Scottish Ambulance Service (SAS). Ambulance service is an integral part of any health care system. They provide critical, life-saving interventions by delivering immediate medical care and rapid transportation to hospitals. An efficient ambulance network potentially improves the survival rates and health outcomes of the patients. Additionally, ambulances are equipped with essential medical equipment such as Automated external defibrillators (AEDs), adrenaline auto-injector (EpiPen), etc, which are extremely useful when a patient is suffering from cardiac arrest or allergic reaction. However, in most of these scenarios, response time is a crucial factor as the survival chance of a patient decreases rapidly over time. This is particularly challenging as the first responders can face high volume of traffic whilst moving or their base location is far away from the place of incident. Therefore, to tackle this issue, we propose a drone assisted service that can provide emergency equipment till the first responders reach at the place of incidence. This way, we can reduce the chance of death especially for patients with cardiac arrest or allergic reaction.

The main purpose of this analysis is to show that sending a small unmanned vehicle whilst the ambulance reaches the place of incidence can help in many life threatening situations and possibly increase the chance of survival. To do so, we first use a surrogate modelling based strategy to obtain drone flight time as well as battery consumption to evaluate performance of a drone under different conditions. Then use a genetic algorithm based approach for facility allocation using historical data where our design thresholds are dependent on the flight surrogate. Finally, we construct a probabilistic metric of completing a mission which gives the reliability of the drone network for emergency response in different time of the year.

The rest of the paper is organised as follows: in Section 2 we give a brief summary of the cardiac arrest calls in Scotland and our specific region of interest under the operation of 'NHS Grampian'. Followed by our modelling strategy for the emergency response using drone in Section 3. Section 4 shows our analyses for the region supervised by NHS Grampian and finally we conclude our paper in Section 5.

2. Cardiac Arrest Statistics of Scotland

In this section, we look into the cardiac arrest statistics of Scotland from 1st April, 2022 to 31st March 2023. In this

*E-Mail: tathagata.basu@strath.ac.uk

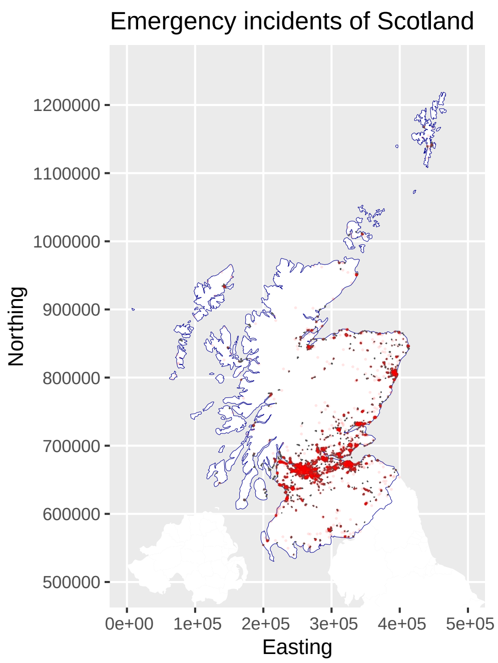

Figure 1. Emergency calls recorded in Scotland from 1st April 2022 to 31st March 2023.

period, there are a total of 3514 calls were recorded where a patient suffered from cardiac arrest. These calls were made predominantly from the urban areas where majority of the people reside. In Fig. 1, we provide the distribution of these recorded calls across Scotland. Note that due to the sensitivity of the content, we only present masked data. We can see that there is a huge cluster of calls near the southern part of Scotland. Most of these calls were made from Glasgow and Edinburgh, the two biggest cities in Scotland. Therefore, if we want to find an optimal drone network for emergency response then the majority of the algorithms will give us nodes which are near Glasgow and Edinburgh. However, this contradicts our mission of serving remote areas of Scotland as well. Therefore, we consider sub-regions of Scotland for the design of the network.

Instead of using a clustering algorithm, we simply consider these sub-regions based on NHS Scotland's operation. There are a total 14 such sub-regions and in our analysis, we will work with NHS Grampian. This test case is particularly interesting as it is one of the biggest boards in terms of area and has a major city which records a significant number of calls. Therefore, this board can be seen as a representation of Scotland in terms of the distribution of emergency calls in rural and urban areas.

In Fig. 2, we provide the operation area of NHS Grampian. The grey lines show the major roads in Grampian and the '+' symbol denotes an ambulance station. Based on the road network and the location of the ambulance station, we compute the shaded region which denotes the ambulance coverage in 6 minutes. We also provide the emergency call locations in Grampian. We see

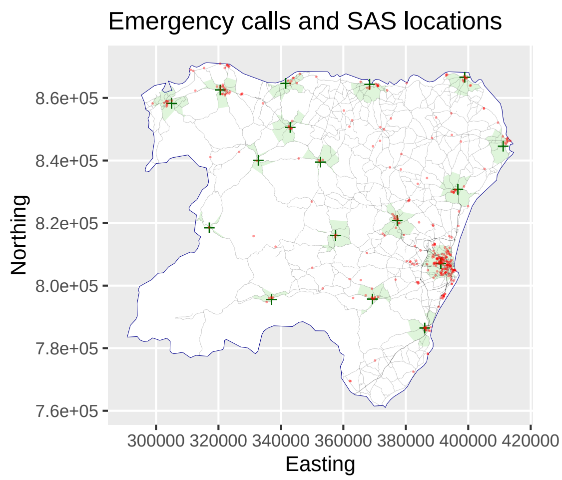

Figure 2. Emergency call distribution and Scottish ambulance service network of Grampian

that there's a big cluster on the eastern border of Grampian where Aberdeen is situated, a major city of Scotland.

3. Modelling

The modelling of emergency response network is done in two steps. First we construct a surrogate model to estimate drone flight time and battery consumption to obtain important metrics that we will be used to select design metrics for the drone logistic network. Then we use a genetic algorithm based method to design the drone logistic network.

3.1. Surrogate Model for Flight Time

We generate our training dataset using a high fidelity simulator of a quadcoptor drone with the following properties:

- **Nominal speed:** The drone operates at a nominal speed of 30 m/s under no wind conditions.
- **Battery configuration:** The drone is equipped with two different batteries, each dedicated to specific flight phases:
  - *Vertical movement battery:* This battery (4 mAh) is exclusively used for powering the vertical movements such as take-off and landing.
  - *Cruise battery:* This battery (10 mAh) is used during the cruise (horizontal) phase of the flight.

We then use these training dataset to create Gaussian process [6] based surrogate models.

Design Parameters: For the design of the surrogate model, we consider six different modelling parameters: distance, wind speed, wind angle, elevation change, direction change, mass of the payload.

- *Distance:* The total distance the drone needs to travel from the point of departure to the destination. Clearly, longer distances result to longer flight times and higher battery consumption.
- *Wind speed:* The speed of the wind encountered during the flight. Higher wind speeds might require the drone

to use more energy and hence result to higher battery consumption.

- *Wind angle:* The direction of the wind relative to the drone's flight trajectory. Depending on whether the wind is a headwind, tailwind, or crosswind, it can either reduce or increase the total flight time.

- *Elevation change:* The total variation in altitude that the drone must cover during its flight. Changes in elevation requires more power usage, as well as longer flight time.

- *Direction change:* The total amount of degrees of changes in the flight trajectory. This alters the relative wind angle and therefore plays in important role in battery usage as well as flight time.

- *Payload mass:* The weight of the object the drone is carrying. The payload mass directly affects the drone's energy consumption, as a heavier load requires more power to lift and maintain the flight.

Parameters of Interest: Using the surrogate models we are interested in estimating the *total flight time* and the *battery consumption*. However, the total flight time itself may not be a stable parameter. Instead we consider three major legs of a flight and estimate the corresponding completion time.

- *Take-off:* The initial phase where the drone ascends to its cruising altitude. This stage requires substantial energy from the vertical movement battery to lift the drone off the ground and reach a stable height. Usually, the time is proportional to the wind speed and cruise altitude and higher wind speed leads to longer take-off time.

- *Cruise:* The middle phase where the drone travels horizontally at its nominal speed of 30 m/s (in ideal condition). During this stage, the cruise battery is primarily utilised. In this phase the distance plays a crucial role as well as wind direction.

- *Landing:* The final phase where the drone descends from its cruising altitude to the ground. Similar to take-off, this phase also relies on the vertical movement battery to control the descent rate and ensure a smooth landing.

Results: We generated a total of 250 samples using the high fidelity simulator for training and additional 50 samples for testing. We provide the prediction accuracy in Fig. 3. We show the estimated time in blue and true time in red. We found that total 5 cases are not within the 95% confidence interval. However, in three of those cases, our model over estimates the time therefore, we refrain from tuning the Gaussian Process parameters as in reality this leads to a more conservative model which is important for risk analysis.

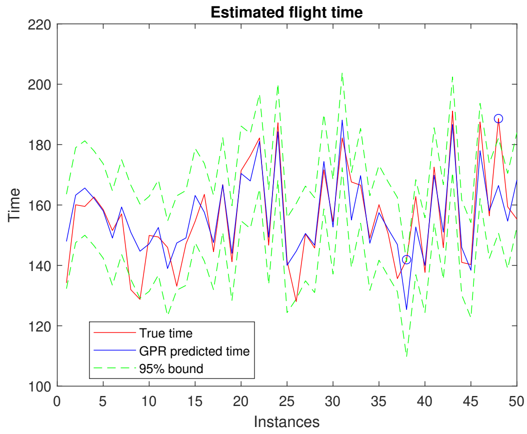

Figure 3. Estimated flight times for the test dataset.

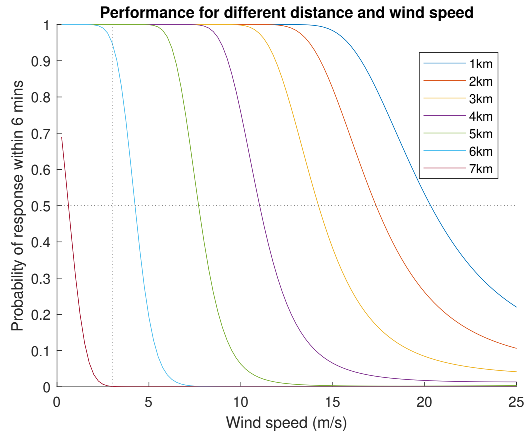

Figure 4. Probability of responding within 6 minutes

We also perform a sensitivity analysis of our surrogate model under different wind speeds and different distances. We show our result in Fig. 4. The vertical dotted line is the minimum wind speed (3 m/s) we should expect and the horizontal dotted line is the 0.5 probability that the drone will respond within 6 minutes.

3.2. Station Allocation

For finding the optimal location of the drone stations we use a data driven approach. We first discretise the area in small squares of area 1 sq. km. Then we count the total number of emergency calls recorded in that block. This way, for a given coverage threshold ν and time threshold τ, we can create the following optimisation problem:

$$\begin{aligned} &\min_{n>0,x,y} && n \\ &\text{s.t.} && \sum_{i=1}^{n} \#((t_{i,e}) \leq \tau) \geq \nu N/100, \;\; \forall i \in I, e \in E \end{aligned} \tag{1}$$

where N is total number of cases in that region.

This can be seen as an iterative volume maximisation algorithm. That is, we assign a drone station i and count the total number of emergency calls e which can be responded with τ time. We stop our optimisation when we cover at least ν percent of all the cases.

Now, based on the analysis in previous section, we can assume a drone can fly upto 6 km within 6 minutes under moderate wind. We also assume that a drone is always available at the drone station. Therefore, we set $\tau = 360$ and for any case that occurs with 6 km of the drone station can be covered in tau seconds. Finally, we set $\nu = 90$ as a desirable percentage of cases to be covered.

3.3. Reliability Analysis

The conditions used to create the drone logistic network can be seen as a best case scenario. However, in reality this may not be the case. Therefore, to evaluate the reliability of the drone logistic network, we propose the following probabilistic metric

$$\rho = P(t < \tau)(1 - P(F))P(b > 0). \qquad (2)$$

Here, the first component denotes the probability that a drone can complete the mission within 6 minutes. For this,we use our surrogate model for drone to estimate the probability. The second component denotes the probability that a drone can finish the task without any mid-air failure. To model this, we consider an exponential distribution so that a drone is expected to fail after 500 hundred hours of constant flying [7]. The third component denotes the probability that the battery does not run out and can complete the task successfully. This is also evaluated using our surrogate model.

Another metric, we consider on the side is the survival of the patients of cardiac arrest. According to the report of National Institute for Health and Care Excellence [8], the probability of survival to hospital discharge reduces by 10% in every minute of delay. We use this to construct the following probabilistic metric

$$SP(patient \mid t) = (0.9)^{\frac{t}{60}} \qquad (3)$$

where SP stands for survival probability.

4. Analysis

As mentioned earlier, we want to analyse the area under governence of NHS Grampian which comprise of three different administrative councils of Scotland, which are ‘Moray’, ‘Aberdeenshire’ and ‘City of Aberdeen’. The region includes 88 major settlements, is monitored by 17 ambulance stations operated by Scottish Ambulance Service (SAS). In this region, SAS received 349 emergency calls from 1st April 2022 to 31st March 2023 which we show these locations in Fig. 2.

4.1. Network Design

We perform our optimisation algorithm as described in Section 3.2. We notice that we need at least 20 drones to cover 90% of the previous cases with a nominal coverage of 6 km in 6 minutes. We show these drone stations in Fig. 5. We also perform another analysis where we consider the 17 Scottish ambulance stations as initial drone stations. Then we optimise to add further drone stations to reach our desired threshold of coverage. We notice that in this case, we need 10 additional drone stations to construct the drone logistic network. That is, we need total 27 drone stations to

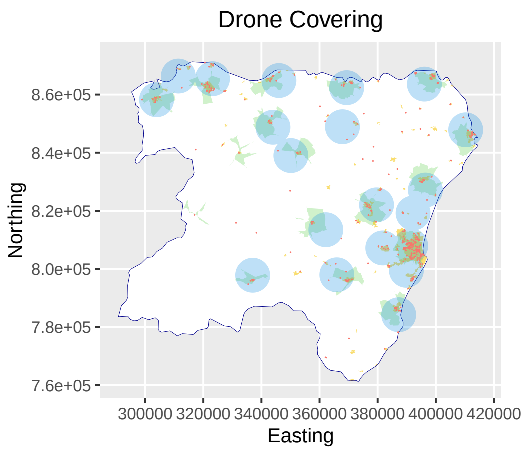

Figure 5. Drone station locations based on historical data

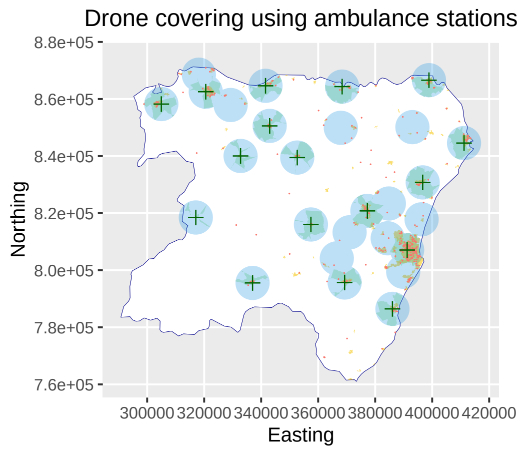

Figure 6. Drone station allocation using SAS stations

cover 90% of the cases. This also shows that, we may only use a few of these ambulance stations instead of considering all 17 to achieve the threshold with fewer number of drone stations. We show this result in Fig. 6.

We also provide a brief comparison in Section 4.1, where the first column shows result for optimised design and the second column shows result for the SAS based design. We also provide the total population settlement area covered in the second row and the total land area covered in third row. Clearly, SAS based design covers more area as we have more number of drones present in the network.

Table 1. Comparison of optimised design and SAS based design

	Optimised DS	SAS and DS
No. of DS	20	27
Population (%)	81.95	86.83
Area (%)	22.83	29.66
Case (%)	90.54	90.26

4.2. Reliability Analysis

To demonstrate our approach and perform a reliability analysis, we show the result for the first 10 recorded data. Clearly, all of them occurs during the spring time as the

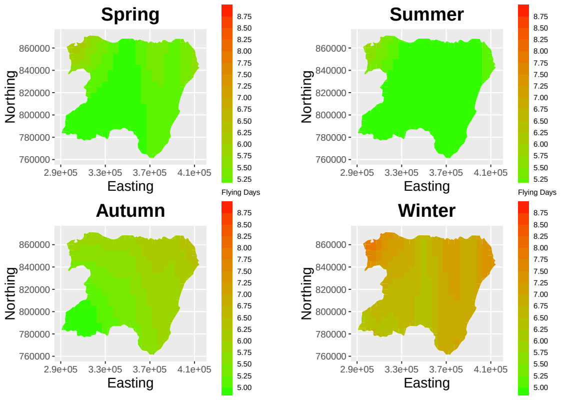

Figure 7. Drone station allocation using SAS stations

incidents are recorded with respect to time. However, we consider all four season to evaluate the reliability of the system. To do so, we first construct a wind model using Met Office UK data. We show this wind surrogate in Fig. 7. We can see that the wind speed tends to be higher during and autumn and can be very harsh during winter. Ideally, we would like to use specific wind speed for each case. But for the sake of illustration we consider the average seasonal wind speed, which is 5.1 m/s in spring; 4.8 m/s in summer; 5.6 m/s in autumn; and 6.9 m/s in winter.

Based on these, we compute the seasonal reliability of our system and show that in Section 4.2. In the table we put asterisk for 5th and 6th case because we have a report of two cardiac arrests at the same location and at the same time. For this particular case, we use the payload mass to be twice of others. As we can put two defibrillators in the same drone. Based on this analysis, we see that we can achieve a reliable system with reliability index being over 0.7, except for the 8th case. For this particular case, the nearest drone station is about 5.7 km away. Therefore, the reliability of responding within 6 minutes is very low during winter and significantly low during spring.

Table 2. Reliability of the system in different seasons

Dist(km)	Spring	Summer	Autumn	Winter
3.1	0.9991	0.9992	0.9991	0.9991
4.7	0.9989	0.9990	0.9987	0.9704
5.1	0.9952	0.9979	0.9747	0.7048
4.0	0.9990	0.9990	0.9990	0.9989
5.0*	0.9976	0.9986	0.9879	0.7915
5.0*	0.9976	0.9986	0.9879	0.7915
2.5	0.9992	0.9992	0.9992	0.9992
5.7	**0.5600**	**0.6890**	**0.3342**	**0.0601**
1.4	0.9994	0.9994	0.9993	0.9993
4.0	0.9990	0.9990	0.9990	0.9989

We also show our estimated response time and compare with the recorded response time in Section 4.2 where the first column shows the recorded response time and the next four columns show the estimated time in different seasons. We notice that our estimated response time is usually within the desired threshold of 6 minutes. However, we also note that for 3 different cases the recorded response time is better than us one being only 2 minutes which is almost impossible to achieve with a drone because of its operational process.

Table 3. Estimated response time in different seasons

SAS	Spring	Summer	Autumn	Winter
1320	254	251	260	274
1200	317	314	323	337
180	333	330	339	354
240	291	288	297	311
360*	330	327	336	350
360*	330	327	336	350
120	229	225	235	249
1200	358	355	364	379
300	188	185	194	208
480	291	287	297	311

Finally, in Section 4.2 we show the survival probability of the patients after hospital discharge. We notice that for all the cases, we manage to achieve an estimated probability higher than 0.5. This is particularly promising as, for patients with shockable cardiac arrests, early use of defibrillators can be the deciding factor in future outcomes. Therefore, sending a drone whilst the ambulance is on the move can be a good alternative to current system, which solely rely on the ambulance.

Table 4. Estimated survival probability of the patients

SAS	Spring	Summer	Autumn	Winter
0.10	0.64	0.64	0.63	0.62
0.12	0.57	0.58	0.57	0.55
0.73	0.56	0.56	0.55	0.54
0.66	0.60	0.60	0.59	0.58
0.53*	0.56	0.56	0.55	0.54
0.53*	0.56	0.56	0.55	0.54
0.81	0.67	0.67	0.66	0.65
0.12	0.53	0.54	0.53	0.51
0.59	0.72	0.72	0.71	0.69
0.43	0.60	0.60	0.59	0.58

5. Conclusion

In this paper, we explore the possibility of integrating drones in emergency response systems. We perform a data driven facility allocation optimisation to design the drone logistic network. Moreover, we exploit the use of high fidelity simulator to create realistic surrogates to assist the thorough examination of system reliability under varying weather conditions. We provide our analyses for specific region to show the applicability of a our approach to enhance the emergency response service.

Moving into this direction, in future we would like to improve several areas of the network design. First and foremost, a detailed analysis of nearby cases could provide valuable insights into the practical application of a drone assisted emergency response and other design considerations such as having multiple drones in a single station. We also want to assess the network's resilience to unexpected demands (such as accident, fire, etc) which is crucial for ensuring robust performance in many real-world scenarios. Last but not the least, we wish to conduct comprehensive cost analyses and evaluate the environmental impacts of using drones to ensure a sustainable economic and ecological alternatives.

Acknowledgment

This work is funded by the project CAELUS, UK Industrial Strategy Future Flight Challenge Fund.

References

[1] I. Quintanilla García, N. Vera Vélez, P. Alcaraz Martínez, J. Vidal Ull, and B. Fernández Gallo, "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*, vol. 5, no. 1, 2021. [Online]. Available: https://www.mdpi.com/2504-446X/5/1/13

[2] T. K. Amukele, J. Street, K. Carroll, H. Miller, and S. X. Zhang, "Drone transport of microbes in blood and sputum laboratory specimens," *Journal of Clinical Microbiology*, vol. 54, p. 2622–2625, 2016.

[3] Matternet, "Matternet launches drone delivery operations at labor berlin in germany," 2020.

[4] G. Li, Z. Liu, J. Hu, and H.-J. Li, "Leonardo, telespazio and bambino gesu' children's hospital test the use of drones for biomedical material delivery," 2020.

[5] P. Walker, live flight trials of Scottish medicine-transporting drones completed. [Online]. Available: https://www.insider.co.uk/news/live-flight-trials-scottish-medicine-31349726

[6] C. Williams and C. Rasmussen, "Gaussian processes for regression," in *Advances in Neural Information Processing Systems*, D. Touretzky, M. Mozer, and M. Hasselmo, Eds., vol. 8. MIT Press, 1995. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/1995/file/7cce53cf90577442771720a370c3c723-Paper.pdf

[7] R. Brewer, "Responsible drone flying: A risk assessment." [Online]. Available: https://committees.parliament.uk/writtenevidence/101516/pdf/

[8] NICE, cardiac arrest - out of hospital care. [Online]. Available: https://cks.nice.org.uk/topics/cardiac-arrest-out-of-hospital-care