UAV deployment for flood-resilient mobile networks: a data-driven analysis for the Netherlands

JULIAN ADAMSE, University of Twente, The Netherlands

Although the risk of a flood is perceived as low in the Netherlands, it might still result in significant disruptions in critical services. Due to climate change, the chances of a flood might even grow. During a flood base stations (BSs) can be damaged and cease to function. The failing of BSs will lead to people not being able to connect to the network. In an emergency, this can be dangerous. We will use data on the layout of the existing cellular infrastructure provided as a list of base stations by the RDI. This is combined with flood maps provided by the LIWO to show the impact floods can have on the network. To help support the network non-terrestrial BSs can be used. These can provide network access in places where the terrestrial BSs have failed. In this research, we will focus specifically on Unmanned Aerial Vehicles (UAVs). UAVs are suitable to supplement a network in an emergency due to their fast deployment time and their ability to access locations that might be inaccessible over land during a flood. This research aims to find deployment positions for the UAVs that maximize the number of people with network access in the event of a flood for a given number of UAVs. To improve the cover provided by the UAVs we will develop an algorithm that decides where to put the UAVs based on which BSs have dropped out. The algorithm will also prevent the overlap of UAVs with BSs and each other to enlarge the area that will be covered by the UAVs. We will compare the new algorithm with a naive version using simulation.

Additional Key Words and Phrases: UAV, Network, Resilience, Flooding

1 INTRODUCTION

During and after flood events, having a stable communication network plays a key role in search and rescue efforts. However, during flooding, cellular network infrastructures might be disrupted as some base stations (BS) in the flooded areas might fail. Such failures reduce the quality and availability of the services offered by a network [2]. For disaster-resilient networks in the face of the anticipated increase in extreme weather events, it is paramount to first understand the resilience of a cellular network and then design strategies to mitigate the identified risks.

In this research, we focus on the resilience of Dutch cellular networks to floods and assess the existing infrastructure by combining the data from the Rijksinspectie Digitale Infrastructuur (RDI) on the cellular network infrastructures and the flood depth levels expected under different climate scenarios from the Landelijk Informatiesysteem Water en Overstromingen (LIWO). As a key performance metric, we consider the number of people that have stable network connectivity as a proxy of service availability.

Unmanned aerial vehicles (UAVs) can replace the failed BSs by restoring the network connections [3]. This research aims to find an optimal deployment for UAVs to restore the resilience of the Netherlands (NL) cellular network in the event of a flood. Our research aims at addressing the following research question: What is the optimal deployment strategy for a given number of UAVs to provide network access to the maximum number of people during a flood in the Netherlands?

- **RQ1**: Given the predictions on flood depths and different climate scenarios, how and in which regions might BSs be affected by floods?
- **RQ2**: Given the BS failures caused by a flood, what is the optimal deployment for a given number of UAVs to provide network access to the maximum number of people?

To answer these research questions we will first perform data analysis on the data from the Rijksinspectie Digitale Infrastructuur(RDI) [5] and the Landelijk Informatiesysteem Water en Overstromingen(LIWO) [4] to find out how floods might affect the NL cellular networks. The RDI provides a list of all BSs in the Netherlands, this list contains the position of the base station as well as the strength, frequency, and angle of their antennas. The LIWO provides maps with the flooding depths. These maps will be further explained in Section 3.1.2. Afterward, we devise a UAV deployment algorithm that takes the number of available UAVs and the locations of the functional BSs as input and determines where UAVs should be deployed to serve the maximum number of people. Finally, we assess the performance of our proposal via simulations to compare our deployment algorithm with existing/naive alternatives. Although there is already research into how UAVs can be used to support a network, this work focuses specifically on the resilience of the network to floods. Following a data-driven approach, we focus on the NL cellular network specifically and incorporate the existing flood depth data into the cellular infrastructure data to assess the potential service loss due to the failing BSs.

The rest of the paper is organized as follows. First, Section 2 overviews the related literature on UAV deployment for disaster resilience while Section 3 describes the following methodology to address the identified research questions.

2 RELATED WORK

On the topic of network resilience [2] gave a good overview of what factors affect network resilience. [3] gives insight into using UAVs to supplement a network that was recently hit by a natural disaster. [1] proposes a line of sight (LOS) model for the UAV connections in an urban grid.

3 METHODOLOGY

We now present the details of our methodology summarized in Fig.1.

3.1 Data Sources

To conduct this research we need information on existing BSs and the chances of flooding at different risk levels.

TScIT 39, July 7, 2023, Enschede, The Netherlands

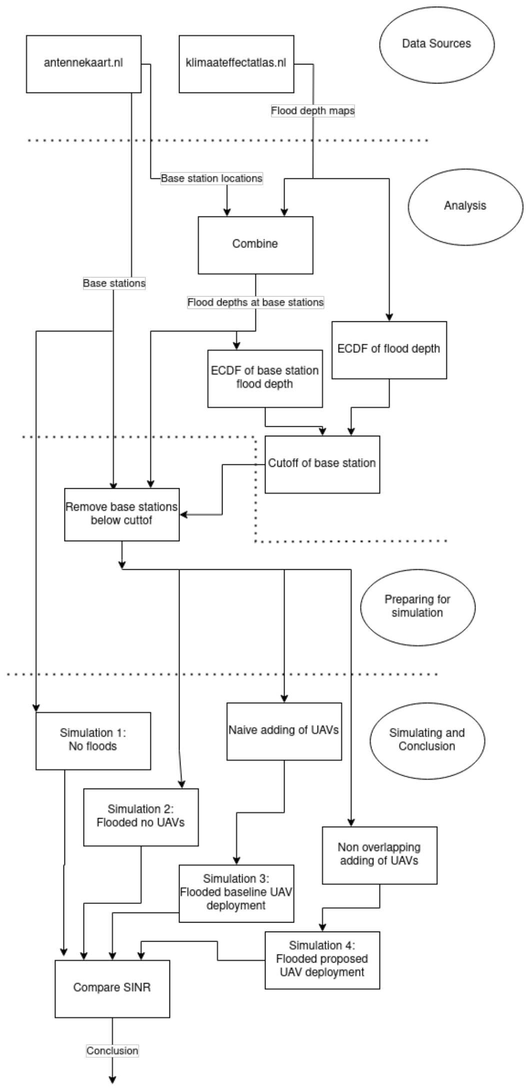


Fig. 1. Schematic overview of Methodology, showing the starting data flowing through different steps to the conclusion, further detailed in Sect. 3

3.1.1 Cellular Network Data. As a source for data on the cellular network of the Netherlands we used [5], which provides a JSON list containing all BSs in the Netherlands with their position as EPSG:28992 coordinates and information on their antenna: heights, strengths, and frequencies.

3.1.2 Flood Data. The flood depth maps of [4] come in different risk levels. These risk levels indicate how often an area is expected to be flooded to this depth. An overview of the risk levels and how often they are expected to occur can be found in Table.1. [4] gives 4 maps, one for each of the 4 risk levels. The map of R0 shows flood depths that are expected to occur once every 100.000 years, R1 shows flood depths that are expected to occur once every 1000 years, R2 shows the flood depths that are expected to occur once every 100 years, and R3 shows flood depths that are expected to occur once every 10 years. These maps show the flood depths with a resolution of 25x25 meters for the area of the Netherlands with the extent of (11825,306750) : (284850,619825) in the coordinate system EPSG:28992.

Risk Level	expected to occur once every
R0	100.000 years
R1	1000 years
R2	100 years
R3	10 years

Table 1. Risk levels next to their expected occurrence [4]

3.2 Analysis

As can be seen in Fig.1, we combined the locations for the BSs and the flood depth maps. We did this by taking the positions of the BSs and looking them up in the depth map to obtain the depths at different BSs. We repeated this for all the risk levels resulting in different scenarios. The goal of this analysis is to quantify under each risk level how many BS will be under a certain flood depth and in which locations. We used this information to form an ECDF of the flood depth at BSs. As can be seen in the figure we used the first quartile, the median, and the third quartile to give values for the critical flood depth at which BSs cease to function. The critical flood depth determines at which flooding height a BS is considered inoperable. Each of these 3 depths was added to the list of scenarios.

3.3 Preparing the simulation

The simulator will take multiple inputs. One of the inputs will be a list of existing BSs to characterize the existing network. We will modify this list to compare different scenarios. To model the flooding scenarios all BSs that are flooded more than the critical flood depth will be removed from the list. To model the deployment of UAVs we will add UAVs back into the list as BSs at points determined by one of the deployment algorithms. As a baseline algorithm, we will use the naive random placement of base stations (RND). This algorithm takes random x and y coordinates in the provided area and places UAVs until it has used up the number of UAVs it can place.

4 PROPOSED UAV DEPLOYMENT ALGORITHM

The proposed algorithm No Overlap deployment algorithm (NOP) will improve the covered area by preventing the placement of a UAV in an already covered area. The algorithm does this by taking a random location and doing a check if any existing BSs overlap with this area. If there are none the UAV is placed there. If there are overlapping BSs then a new random area will be selected until no overlap is found. Two BSs are considered overlapping when they are closer than R to each other, the chosen value of R is 500 meters. The pseudo-code of the algorithm can be found in Alg.1. The big O notation of the proposed algorithm is:

$$O(nm + n^2)$$

where n is the amount of UAVs to be deployed and m is the amount of existing base stations.

Algorithm 1 Proposed UAV deployment algorithm.

```
bss ← list of BSs
N ← number of available UAVs
R ← assumed cover range of BSs
for i = 0 to N do
    for j = 0 to 10 do
        p ← random position in area
        correct ← True
        for bs ∈ bss do
            if ( distance between p and bs) < R then
                correct ← False
                break
        if correct then
            add BS with position p to bss
            break
return bss
```

maximum possible flood depth	11.81
25-th percentile	2.181
50-th percentile	1.29
75-th percentile	0.574
minimum flood depth	0.0

Table 2. Percentiles of possible BS flood depths

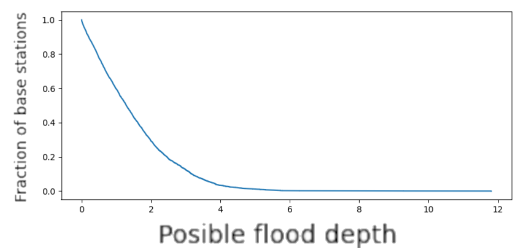


Fig. 2. ECDF showing the flood depth at BSs

5 PERFORMANCE ANALYSIS

5.1 Simulation

To compare the effectiveness of the proposed algorithm to the baseline we use a simulation. The input parameters of the simulator are the municipality that needs to be simulated, the list of BSs provided by the JSON file, percentage of active users (fixed at 2%). The list of BSs was modified according to the parameter of risk level (R), critical flood depth (C), and the number of available UAVs (N). The risk level determines which risk map to use with R0 being rare extreme floods and R3 being the more common floods. The critical flood depth determines at which flood height a BS is considered inoperable. For example, at C1.0 all BSs flooded 1.0 meters or more will be considered inoperable and are be removed from the list of BSs. The number of UAVs determines how many replacement BSs were added back into the list of BSs. We simulated different scenarios.

In the first scenario, we compared the effect of the different risk levels on the existing terrestrial BSs. For each of the risk levels, we created a map showing the effect on BSs at cutoff C0.0. The resulting map showed an upper bound of the damage to the network. The results showed that risk level R3 results in a negligible impact on the BSs 3a. As such we leave it outside of other scenarios.

In the second scenario, we analyze the impact of deploying varying quantities of UAVs. We did this at R1 and C2.2. The cutoff value of 2.2 was chosen as its close to the 25th percentile of the possible flood depth at the BSs. We chose Dronten as a location for this scenario as it is located in the Flevopolder and will be greatly affected by a flood. The bounding box for placing UAVs is defined by points (169106, 496515) and (178657, 510340) EPSG:28992. We chose this bounding box as it fits the area of Dronten. We simulated for N 10, 20, 40, and 80.

For each combination of risk level, cutoff point, and UAV algorithm the simulation was run. The results of the simulation (resilience of the resulting networks) can then be used to conclude the impact of the flooding, naive RND UAV deployment, and NOP UAV deployment.

Fig.2 shows a graph containing the ECDF of the possible flood depth at the BSs. This ECDF has the percentiles that can be seen in Table.2.

An analysis was done of the possible flood depths at the BSs. The percentiles of this showed that the maximum depth a BS can flood to is 11.81 meters. However, most BSs do not reach this depth with 75% of them not being flooded more than 2.181. Table.2 shows all percentiles of possible BS flood depths.

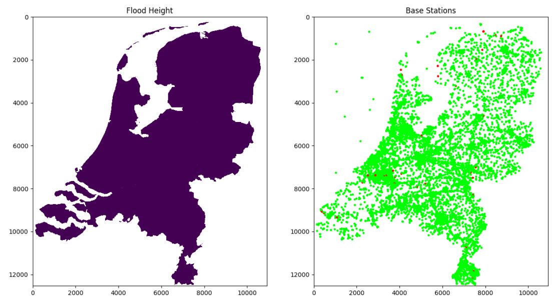
This effect is further illustrated in the ECDF of the possible flood depth at the BSs seen in Fig.2. In this figure, it can be seen that only less than 5% of the BSs can experience more than 4-meter floods.

We also performed an analysis of the maximum impact of floods given the different risk levels. The results of this can be seen in Fig.3. In Fig.3a it can be seen that during the common floods, only individual BSs can be flooded. Fig.3b shows the first cases of multiple BS failures that can affect larger populations of people. Fig.3c shows the results for the Low probability flooding, in these events the BSs in the Flevopolder and Noordoostpolder will also be flooded. The final figure Fig.3d shows the most extreme and rare flooding. Because of the low impact of common floods on the network, we will not consider them further.

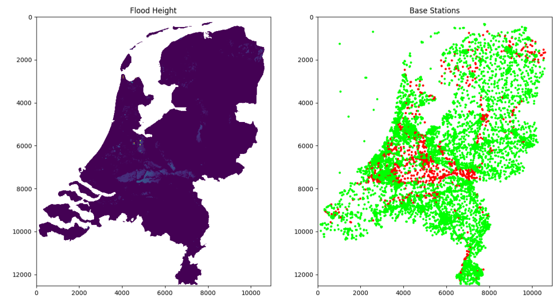
We performed an analysis on the effect of flooding on the fraction of disconnected population FDP . This was done in the area of Dronten which has major flooding at R0 and R1. The test was done at cutoff points C1.3 and C2.2 and risk levels R0, R1, and R2. The test was also done without flooding. The results of this can be seen in Fig.4.

We also performed a comparison of the effect of different numbers of available drones on the difference in FDP between the RND and NOP algorithms. Fig.5 shows the results of this comparison.

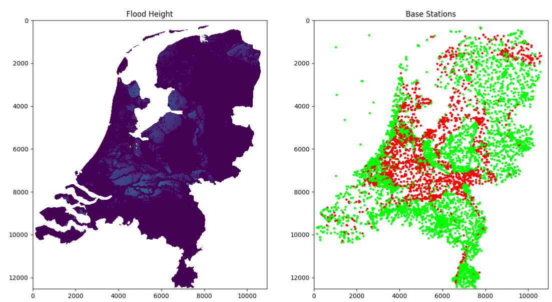
We also performed the comparison between the impact on different providers which can be seen in Fig.6a and Fig.6b for the FDP and FSP respectively.



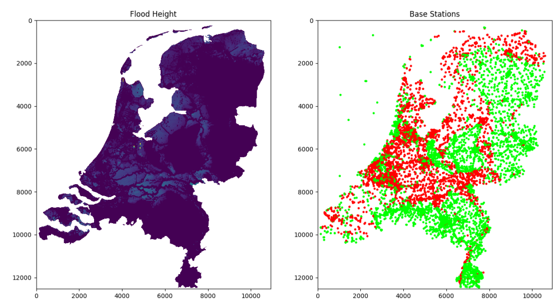
(a) R3(common) C0.0.



(b) R2 C0.0



(c) R1 C0.0



(d) R0(rare) C0.0

Fig. 3. Maps showing the distribution of failing BSs due to floods at four risk levels: (a) high (b) medium (c) low, and (d) negligible.

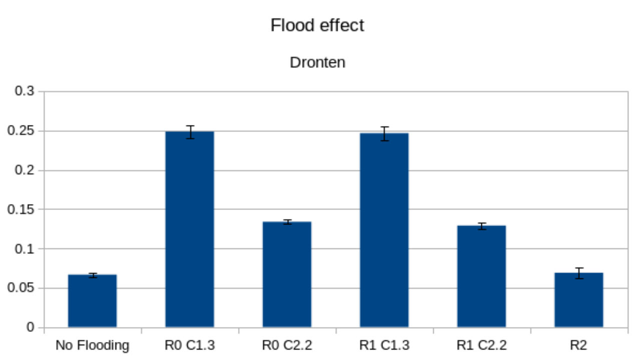


Fig. 4. FDP of different risk levels and cutoff points for Dronten

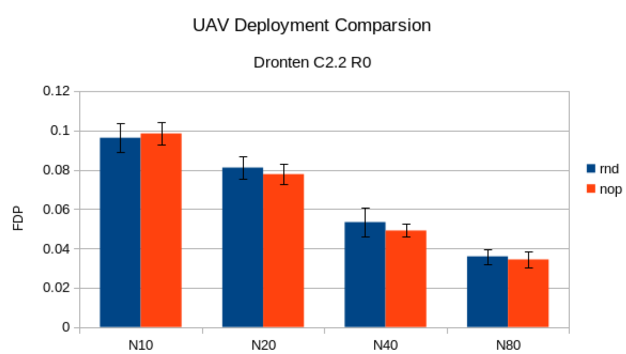


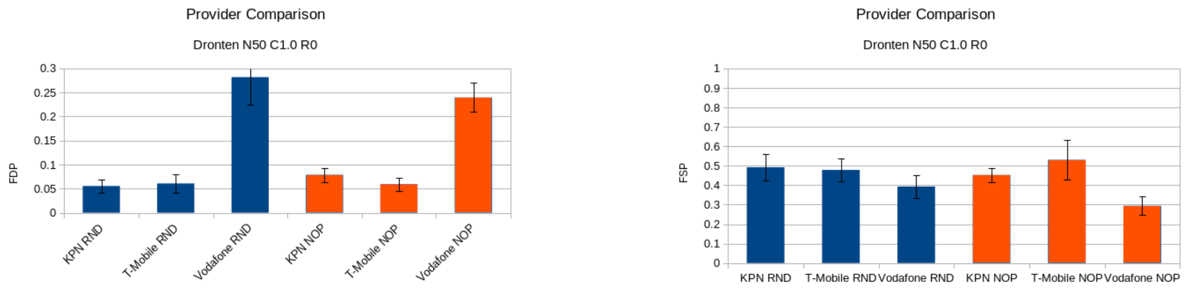
Fig. 5. Comparisons between RND and NOP algorithms

6 CONCLUSION

6.1 Flood Impact

Our results show what effect flooding can have on the cellular network of the Netherlands. As can be seen in Fig.3a common floods do not have enough effect to benefit from UAV deployment. During common floods(R3) BSs that malfunction will always have another BS nearby. However, the rarer floods (R2 and rarer) already start having an effect. As can be seen in Fig.3b there are larger areas in which no BSs are left. Particularly around the river De Lek. This can have a significant effect on the availability of the network in those areas. The results from Fig.2 show that most of the flooded BSs are flooded less than 1.29 meters.

There are low-risk areas and high-risk areas where floods are more common. Even though the chances of a flood might be low, the risk, however, is high as the consequences for the network are large.



(a) FDP (b) FSP

Fig. 6. Comparison on FSP and FDP of different providers/algorithms with a 95% confidence interval

6.2 Algorithm Effect

The results in Fig.5 show that for a small number of deployed UAVs, the NOP algorithm likely does not perform better. This is likely due to the low chance of overlap with a small number of BSs. For higher numbers of deployed UAVs, (particularly N40), our results for NOP deployment were better than those for RND. With NOP performing 4.3% and 8.7% better than RND for N20 and N40 respectively. For the N80 deployment, the differences between the two algorithms start to shrink again to 4.5%. This might be explained by the area becoming completely overlapped with UAVs leading to NOP performing the same as RND.

6.3 Future Work

Future work might include more sophisticated algorithms. One of the major pitfalls of the NOP deployment algorithm is its fallback onto random placement if no more uncovered space is available. An improvement that a more sophisticated algorithm could make is to keep track not only of if an area is covered but how covered, placing a UAV on the least covered point. A second improvement that can be made is to prioritize areas that have a higher population in the placement of UAVs.

Other future work might include investigations into the resilience of BSs to flooding. This research had to assume values at which BSs would break down. A more detailed model of how and at which depths BSs break down will be essential in analyzing threats to our network and measuring the effectiveness of possible solutions.

REFERENCES

[1] Margarita Gapeyenko, Dmitri Moltchanov, Sergey Andreev, and Robert W. Heath. 2021. Line-of-Sight Probability for mmWave-Based UAV Communications in 3D Urban Grid Deployments. *IEEE Transactions on Wireless Communications* 20, 10 (Oct. 2021), 6566–6579. https://doi.org/10.1109/TWC.2021.3075099 Conference Name: IEEE Transactions on Wireless Communications.

[2] D.D. Janssen. 2021. Data-Driven Analysis of Cellular Network Resilience in the Netherlands. (July 2021). http://essay.utwente.nl/86918/

[3] Jialiuyuan Li, Dianjie Lu, Guijuan Zhang, Jie Tian, and Yawei Pang. 2019. Post-Disaster Unmanned Aerial Vehicle Base Station Deployment Method Based on Artificial Bee Colony Algorithm. *IEEE Access* 7 (2019), 168327–168336. https://doi.org/10.1109/ACCESS.2019.2954332 Conference Name: IEEE Access.

[4] LIWO. 2023. Klimaateffectatlas. https://www.klimaateffectatlas.nl/en/

[5] RDI. 2023. Antennekaart. https://antennekaart.nl/kaart