Enabling Information Transmission in Low-Throughput Wireless Channels for Aerial Disaster Monitoring Systems

Julian Zobel*
Multimedia Communications Lab (KOM)
Technical University of Darmstadt, Germany
julian.zobel@tu-darmstadt.de

Ralf Steinmetz
Multimedia Communications Lab (KOM)
Technical University of Darmstadt, Germany
ralf.steinmetz@kom.tu-darmstadt.de

ABSTRACT

The utilization of Unmanned Aerial Vehicles (UAVs) for disaster relief has significantly increased in recent years, especially in the fields of aerial monitoring and communication support. At the same time, research on wireless communication channels between UAVs operating in disaster areas and their base station has been neglected, despite its importance for system operability and information transmission. Therefore, this paper addresses requirements of a suitable data channel on the use case of an Aerial Monitoring System for distributed disaster networks. We put special emphasis on possible applications using low-throughput technologies, like LoRa, to enable information transmission on low-cost hardware without centralized infrastructure, which is highly important for UAV applications in disaster scenarios. Specifically, we propose the aggregation of topology information to reduce message sizes and increase usability under challenging network conditions. Our results highlight that the aggregated monitoring information can be transferred to the base station with reasonable delay and reliability, possible with a low-throughput channel as low as 300 $\frac{bit}{s}$. At the same time, the aggregated information still maintains an adequate representation of the monitored topology of the distributed disaster network.

Keywords

Unmanned Aerial Vehicles (UAV), Aerial Disaster Monitoring, Communication Networks, LoRa, Simulations

INTRODUCTION

Disaster preparedness and disaster relief are two crucial challenges our society has faced and will always face with natural and human-made catastrophes. Especially large-scale natural disasters caused by extreme weather conditions severely increased in recent years due to climate change (Gallucci, 2018; Ranghieri & Ishiwatari, 2014; Toya & Skidmore, 2018; Université Catholique de Louvain (UCL), 2022). The parallel increase of societal reliance and dependence in everyday life on sophisticated but vulnerable *Information and Communication Technologies* (ICT), like always available high-speed cellular networks, constantly aggravate these challenges during and after disasters. In recent years, several events like Hurricanes in Puerto Rico or large floods in parts of Germany highlighted that vulnerability of our existing ICT infrastructure. Severely damaged or completely destroyed landlines and cellular networks lead to a complete communication blackout. This impaired any effort for disaster relief and mitigation, especially in the first few days before provisional solutions to provide even the most basic communication capabilities, such as emergency calls, could be set up (Gallucci, 2018; German Federal Agency for Civic Education, 2021; Kreienkamp et al., 2021; Zorrilla, 2017). Since communication is vital for an efficient disaster relief, researchers all over the world emphasize the need for more robust and resilient infrastructure (Hagar, 2015; Hollick et al., 2019; Kreienkamp et al., 2021; Mori et al., 2015; Toya & Skidmore, 2018; Whittaker et al., 2013). This also includes the need for new approaches and methods to improve communication and mitigate the effects of destroyed infrastructure in a disaster situation (Fehling-Kaschek et al., 2020; Hollick et al., 2019; Mühlhäuser, 2021).

*corresponding author

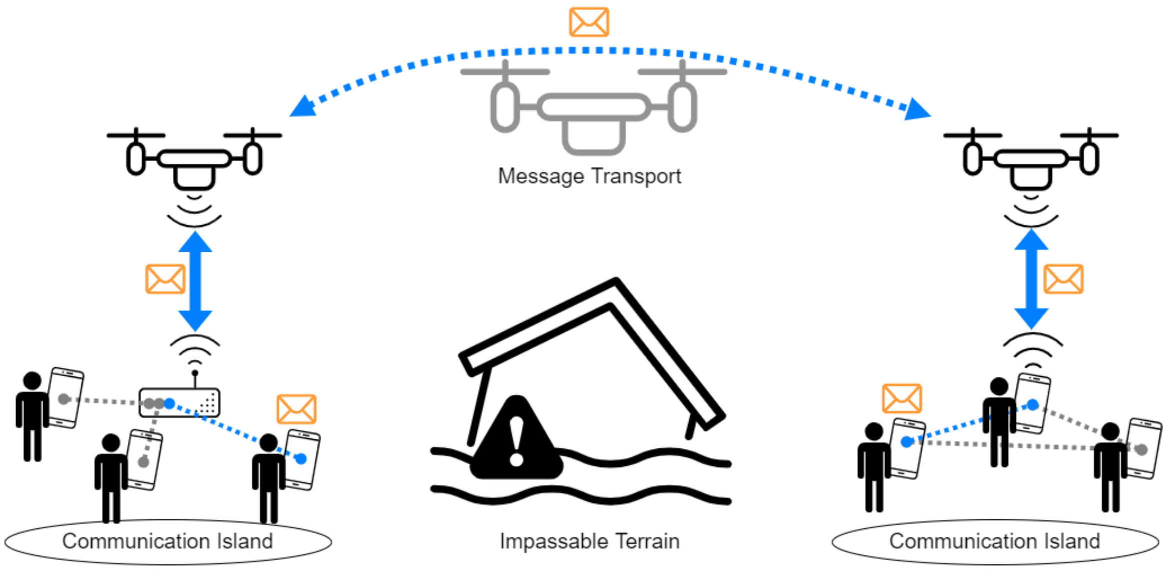


Figure 1. A communication network is separated by impassable terrain, e.g., debris or a flooded area, and traditional ICT infrastructure is not available, resulting in two separated communication islands. The utilization of UAVs as data ferries between the communication islands, independent to the blockades on the ground, provides delayed communication for affected civilians. However, this is only possible when the locations of the communication islands are known to the UAV system. (Flood Icon by Mapps from The Noun Project)

One of these proposed methods to quickly re-establish communication in a disaster area, is the utilization of small, cheap, off-the-shelf *Unmanned Aerial Vehicles* (UAV) as part of a larger aerial communication system. Communication capabilities for first responders and the civilian population can then be restored by providing, for example, a provisional Radio Access Network (RAN) (Chakraborty et al., 2018; Esrafilian et al., 2020; M. Gupta & Varma, 2021; Mahoro Ntwari et al., 2021; Moradi et al., 2018). Such an aerial RAN requires to place a significant number of UAVs over the disaster area to achieve sufficient coverage, demanding a vast amount of resources. Alternatively, UAVs can be used as long-distance data ferries between disconnected communication islands (Bujari et al., 2017; L. Gupta et al., 2016; Lieser et al., 2019; Mozaffari et al., 2017; Zeng & Zhang, 2017), as sketched in Figure 1. This approach requires physical message transport and, thus, provides only delayed message delivery, but is efficiently applicable with only a few available UAVs. In both cases, the provision of communication in the disaster area is paramount for disaster relief efforts and must be executed in the best possible way. Thus, a large part of research focuses on the very important aspects of efficient routing and optimal placement of UAVs. But both problems require precise and up-to-date information on the network topology to find a viable long-term solution. For example, topology information allows to identify communication gaps, which is needed for an initial establishment of routes or finding a suitable placement for access points. Furthermore, the topology in the disaster area may change over time, which requires updates on the topology to enable system adaptivity. The problem is that most research assumes the existence of such information and neglects its active collection, despite the fact that the availability and the acquisition of information from within a disaster area and its transfer to important stakeholders is not an easy task (Hagar, 2015).

In recent years, it was shown that UAVs can be used for the identification of networked communication devices on the ground, e.g., by WiFi or cellular signals (Rubina et al., 2019; Zeng et al., 2019). This ability is utilized in *Aerial Monitoring Systems*, which deploy UAVs to traverse and scan the disaster area to collect information on the network topology. The information is transferred to and collected at the base station, where it is combined and provided to different services, such as rescue services and disaster relief teams working in the area, or a UAV-based communication support system as described above (Arafat & Moh, 2021; Zobel et al., 2022). Similar to visual observation with cameras, signal-based identification and monitoring has a limited range. Thus, this traversal and scanning process of the UAVs is time-consuming, generally increasing in effort with larger disaster areas. Furthermore, the network topology can change over time. As a result, the quality of already gathered information will deteriorate over time without updating it. Therefore, the process must be repeated regularly, resulting in a constant monitoring mission for the *Aerial Monitoring System* (Zobel et al., 2022).

One of the most important aspects for the performance of an Aerial Monitoring System is the transfer of collected monitoring information from the UAVs to the base station. It is, however, also one of the less-researched challenges in this field. In the simplest solution, monitoring data is carried on the UAVs until their return to the base station. There, it is transmitted using physical connections or short-range high-throughput options like WiFi or Bluetooth (Zobel et al., 2022). Carrying collected information back to the base station may even be the only viable option, e.g., when cellular networks are destroyed in the disaster area. Additionally, most cheap, off-the-shelf UAVs do not have cellular or satellite communication interfaces. Due to the possibly long traversal times of a UAV while monitoring an area, carrying information back to the base station comes with the immense drawback of a high Age-of-Information on arrival. This may result in inaccurate or already wrong information given to the base station. Naturally, directly sending monitored information to the base station is a much better choice. But this requires the UAV to have a suitable communication channel, being adequate both in *data rate* to transmit the information fast and in *communication range* to reach the base station in the first place. Without cellular or satellite networks available, the question arises which alternatives for such a data channel can be used instead. New technologies like LoRa, providing robust communication with long communication ranges and low energy consumption, are promising candidates for infrastructure-independent communication in disaster areas. However, this comes with the drawback of small data rates, resulting in a low-throughput channel. Thus, UAVs may be able to reach their base station but probably not to send all monitored information — which requires a tradeoff solution that is yet not researched.

Therefore, this paper investigates the requirements of a suitable data channel for Aerial Monitoring Systems. We focus on the applicability of low-throughput channels like LoRa and possible methods to transmit monitored topology information from a disaster area. Specifically, we show that low-throughput channels are not suited to transfer typical topology information gathered by UAVs or an Aerial Monitoring System. Thus, we propose different concepts for structuring and aggregating network topology information, suitable for monitoring applications and for transmission in low-throughput data channels, respectively. Our concepts and aggregation methods are implemented and simulated in a generalized post-disaster network environment based on previous work (Zobel et al., 2022). With an in-depth evaluation of our concepts, we discuss possible combinations of data aggregation methods and communication channel properties that are suitable for direct data transmission in Aerial Monitoring Systems between monitoring UAVs and base stations on the example of long-range low-throughput communication technologies like LoRa. We show that by using our methods, aggregated monitoring information can be transferred to the base station with reasonable delay and reliability, even with a low-throughput channel bit rate as small as 300 $\frac{bit}{s}$. At the same time, the aggregated information still maintains an adequate representation of the monitored cluster topology of the disaster network. Our approach provides up-to-date information on the network topology, which is critical, e.g., for efficient disaster relief efforts and the resilient provision of a UAV-based communication service in the disaster area to the affected population.

The remainder of this paper is structured as follows. After the introduction and an overview of related topics given in this section, we discuss enablers for data transmission in low-throughput wireless networks as well as concepts for data aggregation and transmission handling. After that, the simulation scenario and the evaluation results are presented in detail, specifically focusing on channel requirements, message sizes, receiving delay, and the quality of representation of topology information from our proposed information aggregation methods. Finally, the paper is summarized and concluded.

ENABLING MONITORING INFORMATION TRANSMISSION FOR LOW-THROUGHPUT NETWORKS

The effective transmission of monitored topology information from Unmanned Aerial Vehicles (UAVs) to their base station is a critical aspect of every Aerial Monitoring System in disaster areas. In this paper, we focus on a post-disaster scenario without working ICT infrastructure, in which a fragmented disaster network based on short-range decentralized device-to-device communication is used (Álvarez et al., 2018; Baumgärtner et al., 2020). The task of the deployed Aerial Monitoring System is to initially detect and subsequently monitor the topology of this disaster network. This information is highly relevant, e.g., for emergency services or UAV-based communication systems, to understand the location and distribution of civilians within the disaster area and efficiently provide support. The areas are scanned using a simple Boustrophedon-style route planning, as sketched in Figure 2. This back-and-forth algorithm is a well-known approach to address coverage path planning problems with deterministic area coverage (Choset & Pignon, 1998; Zobel et al., 2022). Within the scope of this paper, we do not research route planning or how information on a ground-based disaster network is collected in detail. The interested reader is referred to prior work (Zobel et al., 2022) that delves into these topics. Instead, we specifically focus on the transmission of information to the base station *after* its collection on a monitoring UAV. The basic information collected on a UAV consists of the location of a monitored device, a corresponding timestamp of the reading, as well as the network ID of the device itself.

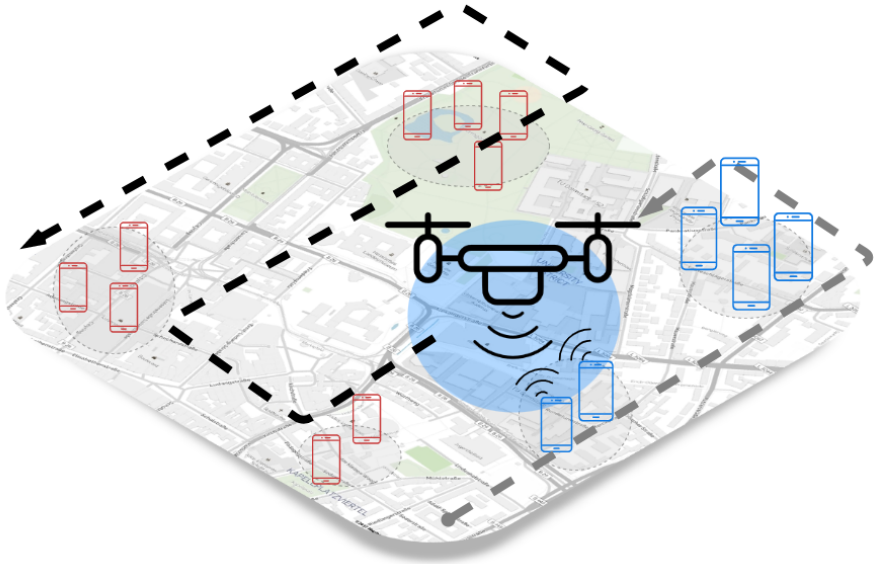


Figure 2. UAV-based detection of mobile devices in a disaster area. Using a Boustrophedon-style coverage path, the entire area is scanned. Devices within reception range of the UAV are detected (blue) by their signals. Due to extensive traversal routes of the UAV, the presence of undetected devices (red) may be unknown for a long time. Similarly, already seen devices can change their position without knowledge of the UAV.

One of the key characteristics of the considered disaster scenario is the highly fragmented network topology of distributed disaster networks (Álvarez et al., 2018). Each of these fragments consists of individual devices that are connected with each other directly or over a multi-hop connection, but not with nodes of other fragments. Thus, we also speak of individual network clusters or communication islands. Due to the distributed nature of the disaster network, however, a monitoring UAV typically encounters individual nodes, not a cluster as a singular entity. Specifically, individual beacon messages of nodes are received while the UAV flies over the cluster. The UAV has to reconstruct the cluster topology based on connectivity estimations or additional information in beacons. For the former, a distance variable D_{conn}, describing the maximum connection distance between ground nodes, can be used to estimate cluster adherence. For the latter, beacon messages can include further information by which ground nodes themselves identify their affiliation to a cluster, e.g., a hash of all known messages (Khelil et al., 2007) or all known cluster nodes (Zobel et al., 2022). Naturally, data that is directly provided by the disaster network itself gives more accurate information, and thus, also a better representation of the actual network topology than a connectivity estimation.

Another limitation in the disaster scenario is that conventional cellular or satellite networks cannot be used at all by UAVs. We expect both communication interfaces not to be available on small and cheap, off-the-shelf UAVs and especially cellular networks to be impaired or entirely not available in the disaster area. However, the LoRa technology[1], a wireless communication technology originally developed for Internet-of-Things (IoT) applications and Low-Power Wide Area Networks (LPWAN), has shown its applicability as an alternative communication technology in disaster networks in recent years (Baumgärtner et al., 2017, 2020). Due to its cost-effectiveness, energy efficiency, adaptivity, and simplicity, LoRa is also increasingly integrated into UAVs and Unmanned Aerial Systems (Ghazali et al., 2021; Saraereh et al., 2020). Nevertheless, the inherent limitation of LoRa lies in its low throughput that comes as a tradeoff with its robust signaling. For typical devices[2], the usable bit rates range depending on the chosen LoRa parameters between 92 bps[3] and 21.9 kbps[4]. Thus, when considering the worst case, it would take a UAV about 0.7 seconds to transmit only a single 8-Byte-location measurement to the base station. Furthermore, this example does not include overhead or other important information, such as the time of the measurement or network information from the encountered network devices. Another heavy restriction is the typical 1% duty cycle of the used frequency bands (European Telecommunications Standards Institute (ETSI), 2018).

[1]Although we use LoRa as a well-researched example in the scope of this paper, our concepts and results are not exclusive to the LoRa technology and could be beneficial in any low-throughput network.

[2]For example, an ESP32 device using the LoRa SX1262 module.

[3]Parameters: 62.5 kHz BW, SF 12, CR 4:8

[4]Parameters: 500 kHz BW, SF 7, CR 4:5

Therefore, the following sections investigate how the transmission process and the structure of topology information can be optimized, to enable its transmission in such low-throughput networks. The objective is to reduce the packet size while preserving the integrity and representativeness of the transmitted data, thereby optimizing the UAV communication process.

Delaying Transmission

Whenever topology information is collected by a monitoring UAV, the question arises at which time this topology information can or should be transmitted to the base station. Intuitively, received information should directly be forwarded to minimize its Age-of-Information (AoI) on reception. This comes especially in mind, in case that information about the entire cluster is shared directly by the disaster network, such as all nodes and their locations within (Zobel et al., 2022). But whenever the cluster changes during the overflight, sending another message would be necessary. The optimal time to send the message is when the overflight of the cluster ends. At that point, the UAV cannot receive any more updates from the cluster, the information is most accurate, and no redundant messages are sent. However, pinpointing this exact time may be impossible. For individual node detection, furthermore, a UAV cannot know when all nodes in a cluster are detected — if that is even possible due to its flight path. Starting with a single node, each measurement must be grouped correctly together with other nodes, that are estimated to be in the same cluster. If a node changes position and the cluster splits as a result, this must also be considered in the process. Directly sending every measurement or every update of a possibly detected cluster or of singular nodes may impose a high load on the communication channel. Waiting for changes for a certain time before sending only the most up-to-date information could, therefore, be highly beneficial.

To address this, a delay λ is introduced, measured for every cluster. Whenever information for a cluster is received at the UAV, this delay is reset. Only when no change in information for that cluster has happened for that time, the cluster information is sent to the base station. In general, a small value for λ reduces the AoI at the base station, but may increase channel utilization due to redundant update messages. A larger delay, on the other hand, reduces information quality due to a larger AoI, but may optimize channel utilization.

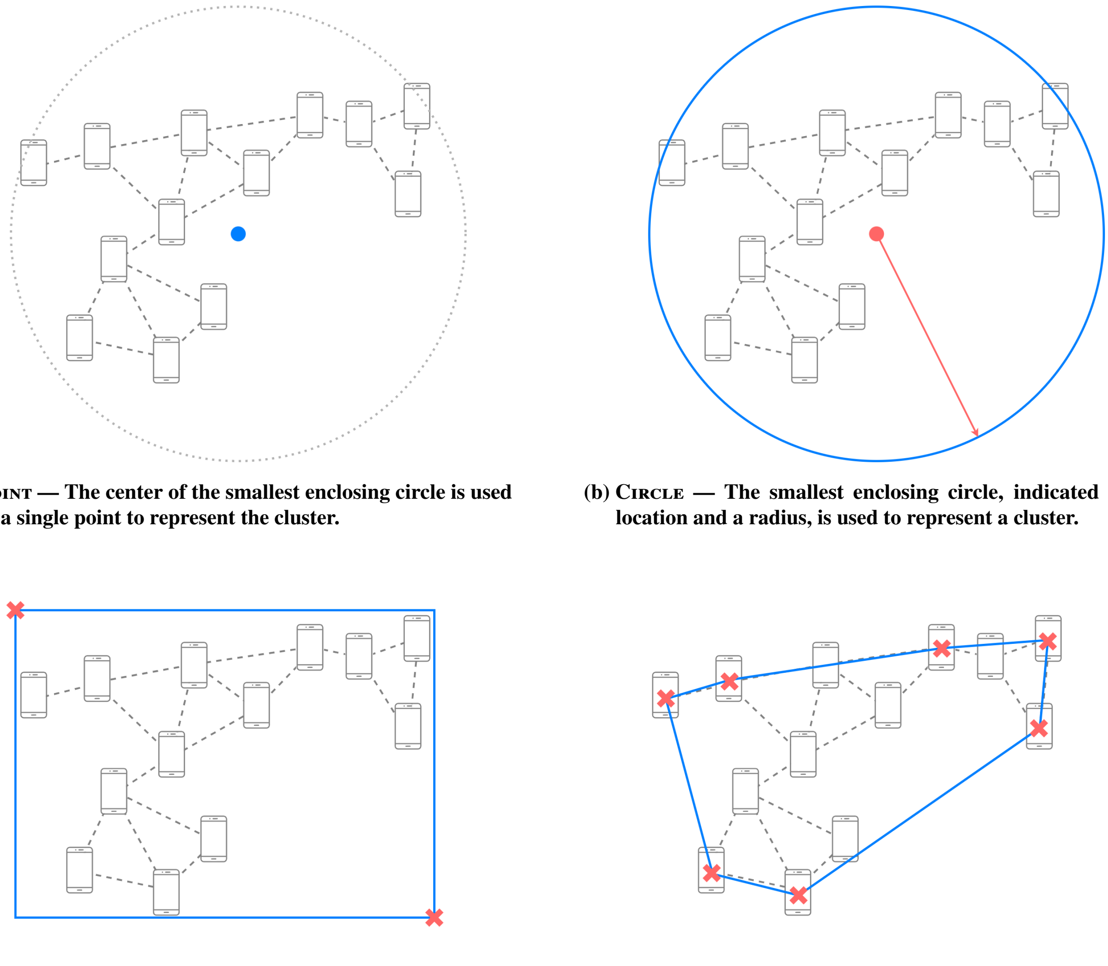
The specific value of λ could, for example, depend on the beacon send interval of the ground-based network. It determines at which rate information can be expected, usually in the range of a few seconds (Álvarez et al., 2018). Whenever nothing is received after a multiple of that interval, information can be sent to the base. When this rate is unknown or cannot be determined by the UAVs, a static λ can be employed. Since typical smaller UAVs fly between 10 m/s to 30 m/s, λ must be chosen accordingly. As an example, $\lambda = 1s$ could be too low to overfly gaps in an oddly-shaped cluster and would lead to several necessary message transmissions, while $\lambda = 10s$ would result in possibly long-left clusters before sending the information. In general, λ must be chosen wisely due to the additional delay that worsens information quality.

The size of λ and its implications are addressed later-on. At this point, however, we note that the impact of λ on the age-of-information of monitoring data is tremendously smaller compared to a solution without a wireless data channel. A physical return for delivery can take a long time, as a single traversal of a monitored disaster area may take 30 minutes or more. Thus, any sensible choice of λ should perform better than a physical data delivery.

Aggregating Topology Information

To enable the utilization of low-throughput channels for topology information transmission, not only the number of messages must be reduced, but also their size. Within the scope of this paper, we are interested in monitoring the clustered network topology in the disaster area. Thus, the exact location of every individual node is not as important as the larger cluster topology they are part of. Furthermore, historic information is not as important as the most current topology. Therefore, only the most recent location of each node is interesting for the cluster topology.

Instead of transmitting every monitored node location as a set of locations representing a cluster, we propose to aggregate the collected monitoring information directly on the UAV before sending. The goal is to reduce the size of the transmitted content as much as possible, while maintaining a suitable cluster representation. To address this, we specifically propose four simple geometric representations with different levels of aggregation: Point, Circle, Bounding Box, and Convex Hull. Figure 3 sketches out each representation with an exemplary disaster network cluster of mobile devices. Each approach provides a different accuracy in terms of representation of the actual cluster and different messages sizes for transmission to the base station. The aggregates are constructed based on the most recent information available to the UAV directly before transmission, i.e., only after the delay λ has expired, as described in the previous section.



(a) Point — The center of the smallest enclosing circle is used as a single point to represent the cluster.

(b) Circle — The smallest enclosing circle, indicated by a location and a radius, is used to represent a cluster.

(c) Bounding Box — The bounding box, i.e., the smallest enclosing rectangle constructed by only two opposing corner vertices, is used as cluster representation.

(d) Convex Hull — The convex hull, i.e., the smallest convex shape enclosing the cluster, is used as representation. The number of required vertices depends on the cluster's shape.

Figure 3. Different cluster representation methods to aggregate topology information and to decrease its transmission size. Blue denotes the representing geometrical shape, red the required information that is transmitted for its representation. The exemplary cluster consists of mobile devices forming an ad hoc disaster network.

Point The Point representation aggregates all cluster information, visualized in Figure 3a by a disaster network cluster of mobile devices, into a single location. This point is calculated as the center of a smallest enclosing circle of all known cluster nodes. Point has the most reduced transmission size with a single location, e.g., being 8 Bytes in size. But this approach also provides the most inaccurate representation.

Circle The Circle representation (Figure 3b) extends Point by the radius of the smallest enclosing circle of the cluster. While increasing the transmission size, assuming 8 Bytes for the center location and another 4 Bytes for the circle radius, this provides a better representation of the cluster and its extents than a single point.

Bounding Box The Bounding Box representation (Figure 3c) uses two vertices to define the diagonally opposed corners of the smallest rectangle, in which all cluster nodes are contained. We align the bounding box in cardinal direction, thus, the horizontal edges are aligned West/East while the vertical edges are aligned North/South, respectively. This representation requires two locations, e.g., each 8 Bytes in size.

Convex Hull The Convex Hull approach, shown in Figure 3d, provides the most accurate cluster representation. Nevertheless, the transmission size can vary greatly, depending on the shape of the convex hull defined by its vertices, each being an 8-Byte location. More complex shapes require more vertices to form the convex hull, thus, also increasing the transmission size significantly.

Increasing Descriptiveness

The proposed approaches can tremendously reduce the transmission size compared to sending all information as individual measurements, especially for large clusters. Nevertheless, the descriptiveness of such detailed information is also lost by reducing it to geometric shapes: information on how many or which nodes are in a cluster, or how old a measured datum is not included in the aggregation from the beginning. We propose to include a single timestamp as minimal information for each aggregate, representing the oldest measurement in the aggregated data set. With this, the receiving base station is, at least, provided with a rough estimate of the data quality and can also differentiate information received at different times or from different sources more easily.

Furthermore, in case that a sufficient data channel is available, the aggregated cluster representations could again be enriched with additional information in exchange for a larger transmission size. As a first option, we can include the number of nodes represented by an aggregate. This only adds a simple and small integer value, but provides a clearer notion of the cluster size, which is valuable information, e.g., for disaster relief efforts to assess the importance of a cluster. However, a requesting service of our Aerial Monitoring System could require individual node information. In such cases, the network IDs of the enclosed nodes in the aggregated representations can be included as a second alternative. Although a valid option, this significantly increases the transmission size again, contrasting our initial goal of reducing it to enable usage of low-throughput networks. Nevertheless, this approach could be a reasonable tradeoff whenever network conditions are just slightly below the requirements for transmitting the entire topology in detail, but adequate with minor reductions.

EVALUATION

The evaluation is conducted in the Simonstrator (Richerzhagen et al., 2015) simulation framework, operating in the extended simulation environment designed for Unmanned Aerial Systems and ground-based Delay-Tolerant Networks (DTNs), as detailed in Lieser et al., 2019. This paper puts special emphasis on the less-researched communication between monitoring UAVs and base station. Thus, we utilize an available implementation of an Aerial Monitoring System from prior work (Zobel et al., 2022), which already includes monitoring UAVs and data collection of a disaster network. The existing implementation is extended by a LoRa channel with configurable data rate. Furthermore, the proposed topology information aggregation approaches and message additions discussed in the previous section are integrated.

Table 1. Simulation Environmental Settings.

Scenario	Map	Inner City, Post-Disaster
	Size	2000 m x 2000 m;
	Node Movement	Civilian Disaster Mobility [a]
	Points of Interest	5, random distribution
	Duration	3 h, 10 random seeds each
Disaster Network	Size	100 Nodes
	PHY	WiFi, IEEE 802.11g
	Range	approx. 75 m
	Data Rate	5 Mbit/s
Aerial Monitoring System	UAV	Quadrotor [b]
	Coverage Path Planning	Lawnmower
	Network Interaction	Cooperative Data Collection [c]
	Monitoring Mission Time	approx. 36 minutes
Monitoring Data Transmission	Aggregation	[None (Cluster), Point, Circle, Bounding Box (BBox), Convex Hull (Hull)]
	Additional Information	[∅, #Nodes, IDs]
	Transmission Delay λ	[None (λ_0), 5s, 15s, 30s, 60s]
	Channel Data Rate	[300 bps, 1 kbps, 21 kbps, 1 Mbps]

[a] cf. Zobel et al., 2021, [b] cf. Zobel et al., 2019, [c] cf. Zobel et al., 2022

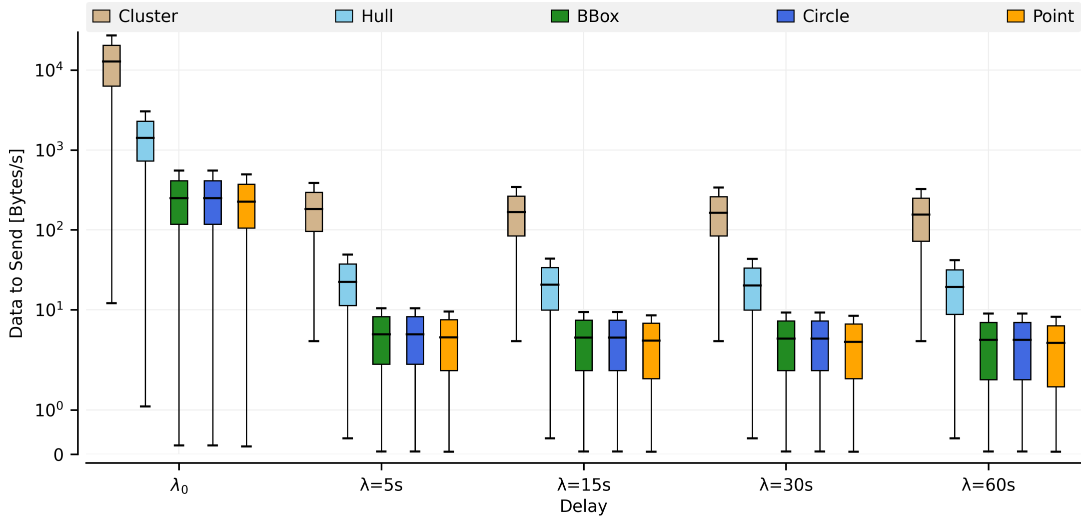
The simulation environment settings, listed in detail in Table 1, encompass 100 mobile devices moving in groups within an inner-city disaster area of 2x2 km^2 (Álvarez et al., 2018; Zobel et al., 2021). For each simulation run of three hours, five points of interest like shelters and first aid stations are randomly selected, with the constraint that they must not overlap and must maintain a minimum distance of at least 300 m from each other. Devices predominantly gather around these points of interest and move in-between them. The mobility model relies on available Open Street Map (OSM) data, limiting device movement to streets and pedestrian walkways mapped in the OSM dataset. Each combination of simulation parameters is repeated ten times with different random seeds.

The entire area is monitored by a single UAV, completely traversing the monitoring area before returning to its base station. Traversal route planning uses a Boustrophedon-style coverage path planning approach (Choset & Pignon, 1998; Zobel et al., 2022), resulting in a total flight time of around 36 minutes from takeoff to landing. Topology aggregation can be switched between the four proposed aggregation methods Point, Circle, Bounding Box, and Convex Hull. Furthermore, the entire cluster information can be send without any aggregation (Cluster). Optional information in aggregates can be omitted (∅), include the number of nodes (#Nodes), or contain a list of all nodes' network IDs (IDs). The transmission delay λ, as described in the previous section, is investigated for no delay (λ_0), reasonably small values of $\lambda = 5s$ and $\lambda = 15s$, and much larger values of $\lambda = 30s$ and $\lambda = 60s$, respectively. Most importantly, we adjust the data rate of the transmission channel towards the base station to investigate requirements on it depending on the used aggregation methods and included detail of information in topology messages. Specifically, we test three settings that represent a data rate similarly achievable by using LoRa: A data rate of 300 bps constitutes the lower bound of possible data rates, 1 kbps a median tradeoff between throughput and signal robustness, and 21 kbps constitutes an upper bound. An additional data rate of 1 Mbps was evaluated as reference comparison for a generic cellular network connection.

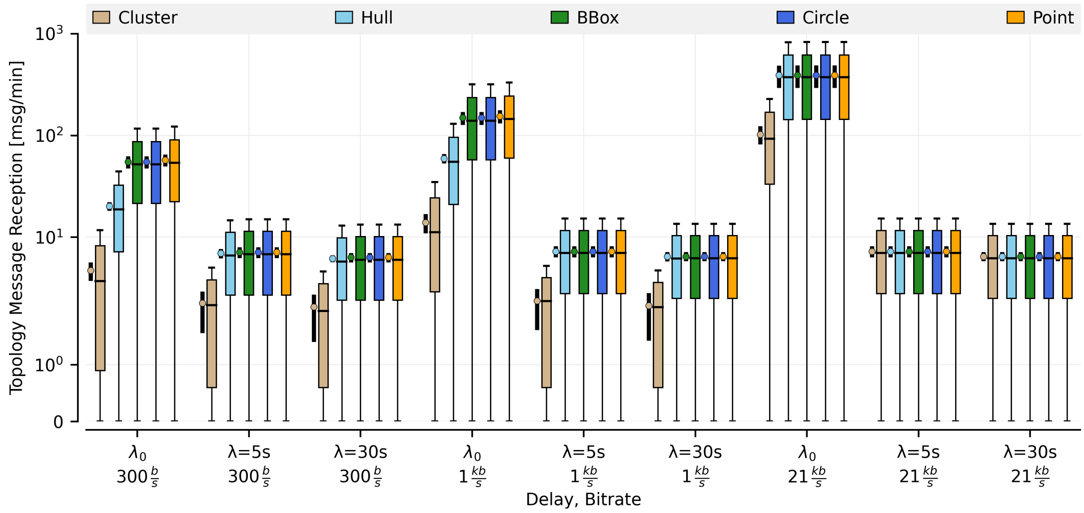
Sender Demands and Actual Throughput

At first, we take a look at the requirements of a monitoring UAV on the channel capacity for sending its information w.r.t. the transmission delay and the aggregation approach. When considering the entire monitoring mission time, the UAV queues between 2.9 and 13.8 messages per second when using direct transmission (λ_0) for around 75% of the time, which is independent of the aggregation approach. When using a transmission delay, however, this significantly reduces to a median of around 0.12 messages per second and to a maximum of 0.25 messages per second. With that, we have a first clue on the expected impact of using a transmission delay and not directly relaying all information received. Additionally, this clearly impacts the amount of data a monitoring UAV wants to send, as visualized in Figure 4a. For direct transmission, sending all information without aggregation would require a median of 13.4 $\frac{kByte}{s}$ but, e.g., only 194 $\frac{Byte}{s}$ with $\lambda = 5s$. At the same time, using aggregation with λ_0 already reduces the amount of data significantly, to around 1.5 $\frac{kByte}{s}$ using convex hulls and even further to around 250 $\frac{Byte}{s}$ for the other approaches. The differences between the transmission intervals, on the other hand, are only in the range of a few bytes per second, slightly decreasing with a higher interval. This suggests that only a few retransmissions were necessary, due to seen topology updates after sending the initial packet. The slight differences between the intervals also suggest that the shorter intervals are already sufficient to track a cluster's topology without requiring multiple topology messages to send during an overflight. Overall, the reduction in both the transmission delay and the aggregation approaches clearly highlights that information can be reduced on the sending side, which tremendously reduces the requirements for the data channel.

Next, we take a closer look at message reception. This clearly depends on the throughput of the channel: with a smaller channel, less messages can be sent and received per time unit. This bottleneck brings several problems, that are (i) an increase of the probability that messages are waiting longer in a sending queue, (ii) that messages are dropped from the queues due to expired waiting times, or (iii) that the queues are already full and new messages are dropped instantly. In the end, these problems are recognized on the receiver, as fewer messages are received than queued to send. Figure 4b visualizes the measured message reception in messages per minute on the base station. As expected from the reduction of sent messages seen in Figure 4a, using a transmission delay obviously decreases the number of messages on the receiving side. However, a larger transmission delay does not impact that number in a more significant way than a smaller delay. In contrary, — especially for the slower bitrate settings on the channel — the number of messages for Cluster and Convex Hull are *lower*, despite a higher number of messages queued on the sender. This already suggests that messages are dropped. With an increase in bitrate, on the other hand, the number of received messages increases for λ_0 for all approaches, while leveling up for Cluster with the other aggregated approaches for a bitrate of 21 $\frac{kBit}{s}$ using a transmission delay. Thus, the number of message drops reduces generally with a higher bitrate, as expected. More importantly, a bitrate of 1 $\frac{kBit}{s}$, which is achievable by state-of-the-art LoRa modules, shows to be sufficient to transmit the aggregated topology information without perceivable message drops.



(a) Throughput demands for sending packets on an unlimited monitoring UAV with different delays. Mind the logarithmic scale. While we perceive a drastic decrease in demand between sending without and with delay, the influence of different delays is minimal.



(b) Received messages per minute on the base station for different delays and bitrates. Mind the logarithmic scale.

Figure 4. Throughput demands for an unlimited sender compared to the received messages on the base station with limited bitrates.

The loss of messages between sender and receiver is further investigated considering Figure 5. As before, a clear decrease in dropped messages with increasing bitrate and with using topology aggregation is perceived. In comparison to direct transmission, only a fraction of messages are dropped due to the smaller number and size of messages, even with a bitrate of only 300 $\frac{Bit}{s}$. These results also support the findings that a data rate of 1 $\frac{kBit}{s}$ is already sufficient for the transmission of aggregated topology information without perceivable losses due to channel capacity. For the Cluster approach, however, this still constitutes for a message loss of around 70%. In addition to the other figures, Figure 5 exemplary visualizes the results for 1 $\frac{MBit}{s}$ data rate to highlight that this is sufficient to send all information without aggregation and loss over the data channel.

Message Size and Optional Message Content

As depicted in Figure 6a, the size of messages is an important factor for their transmission in low-throughput channels. Especially for very large Cluster messages, but also seen in detail for larger Convex Hull messages, these are not received on the base station due to the channel limitations. First with a data rate of 21 $\frac{kBit}{s}$, and supported by the measurements at 1 $\frac{MBit}{s}$ when all messages are received without problems, very bulky messages can be transmitted. The large number of dropped Cluster messages highlights that they are too large in size to be

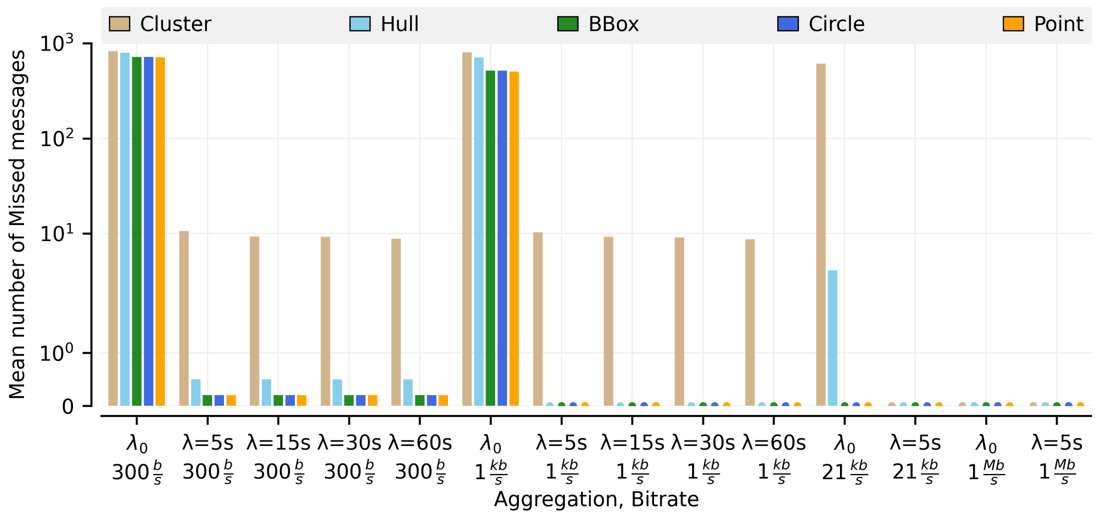


Figure 5. Mean number of missed messages, aggregated over all simulation runs. Mind the logarithmic scale. Round caps indicate zero values. With increasing bitrate and by using topology aggregation, the rate of dropped messages decreases significantly. For aggregated topology information, a data rate of 1 $\frac{kBit}{s}$ is already sufficient for transmission.

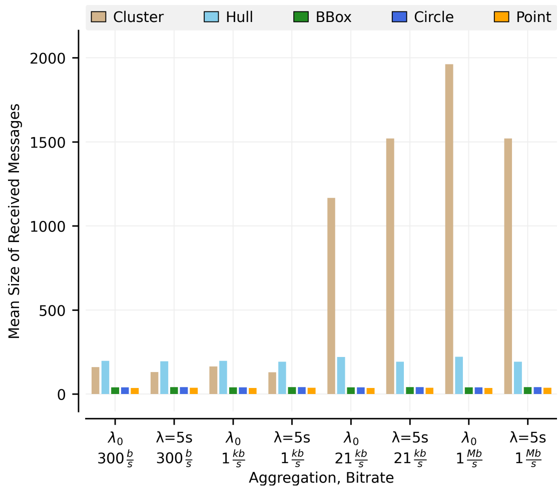
transmitted successfully in low-throughput networks. Thus, the proposed aggregation of information and reduction in size is clearly necessary to allow data transmission for larger clusters in the first place.

In the previous section, we also introduced optional message content in the information aggregates, to increase their expressiveness towards the receiving base station. But we also discussed that, especially including a list of all node IDs, significantly increases the message size, contradicting the intended size reduction. Therefore, Figure 6b takes a closer look of the influence of the optional message content in aggregate messages, on the example of 1 $\frac{kBit}{s}$ bitrate. Clearly, there is no impact by adding a simple integer value for the number of represented nodes in the aggregates, which is also true for a bitrate of 300 $\frac{Bit}{s}$ and the higher bitrates, respectively. For the list of IDs, however, an increase of messages drops is perceivable due to the comparably extreme message size of aggregates. They can increase to more than ten times the size of the same message without these IDs. This increase is especially problematic for the lower bitrate channels, since message drops re-appear for aggregated topology messages with a formerly sufficient bitrate of 1 $\frac{kBit}{s}$ and strongly increase for a bitrate of 300 $\frac{Bit}{s}$. This supports our statement that the list of message IDs should only be added when absolutely necessary and with a sufficiently scaled channel throughput. Preventing message loss and sending the aggregated topology information to the base station is more important than this optional information.

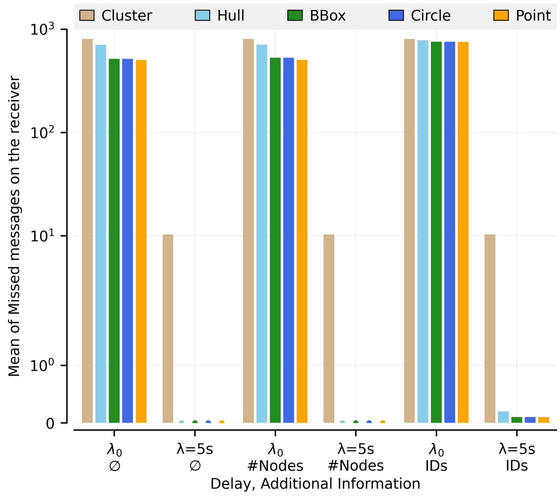
Transmission Time

Another problem with limited channel throughput is the additional delay introduced by filled sending queues. In addition to the actual airtime of a packages, i.e., the time to send the entire package from start to end on the wireless medium, this results in a certain transmission time per packet. To assess this transmission time, we traced the time difference between putting a packet in the network interface's queue on the monitoring UAV and receiving it at the network interface on the base station. This transmission time is visualized in Figure 6c.

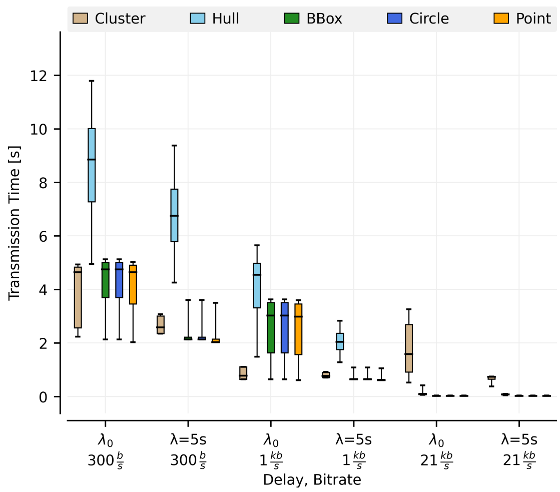
Directly perceivable is that transmission times are generally higher for direct transmission than for a delayed transmission. This comes as a direct result of longer sending queues, which increases the delay for all messages. Furthermore, messages for Convex Hull are clearly more delayed than other types. This can be attributed to their significantly larger size compared to the other aggregation approaches. Therefore, they take longer to transmit and extend the waiting time in the queue for all messages. For the other aggregation approaches, only slight differences can be seen from the results. Curiously, transmission times for Cluster messages are much lower for 300 $\frac{Bit}{s}$ and 1 $\frac{kBit}{s}$ bitrate. Nevertheless, Figure 6c only depicts the time for *received* messages — and, as seen before, these are only the small ones. Larger messages are only received for 21 $\frac{kBit}{s}$. With that bitrate, the transmission time increases again because most messages are now countable for the transmission time. Similarly, nearly no delay is introduced for the aggregated approaches by the queues, indicating empty queues and nearly instantaneous transmission.



(a) Average size of received messages per bitrate and delay transmission. With a higher bitrate, very large CLUSTER and CONVEX HULL messages can be transmitted.

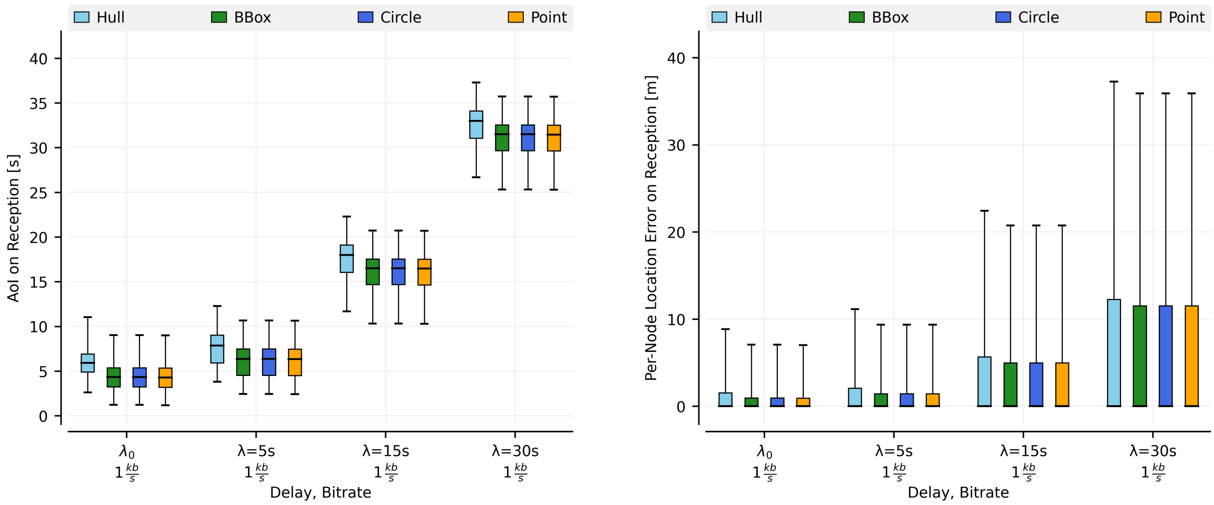


(b) Missed Messages per optional message content, using a data rate of 1 kbps. Using aggregation, only CONVEX HULL results in a few message drops for ∅ and #Nodes. When sending a list of all node IDs, however, the number of message drops increases intensely for direct transmission, and slightly for $\lambda = 5s$.



(c) Transmission time as difference between message insertion at the sending queue on the UAV and message reception at the base station. Only received messages can be counted with this metric, which must be considered when assessing this time difference especially for larger messages and smaller bitrates.

Figure 6. Received message size, missed messages on the receiver for optional message content, and transmission time. The results highlight that the proposed aggregation methods enable transmission via low-throughput data channels in contrast to sending all data.



(a) The age of monitored information when received on the base station, measured per node information aggregated on the monitoring UAV.

(b) The location error of information received on the base station, measured per node information aggregated on the monitoring UAV.

Figure 7. Per-node Age-of-Information and absolute location error on reception for a data rate of 1 $\frac{kbit}{s}$.

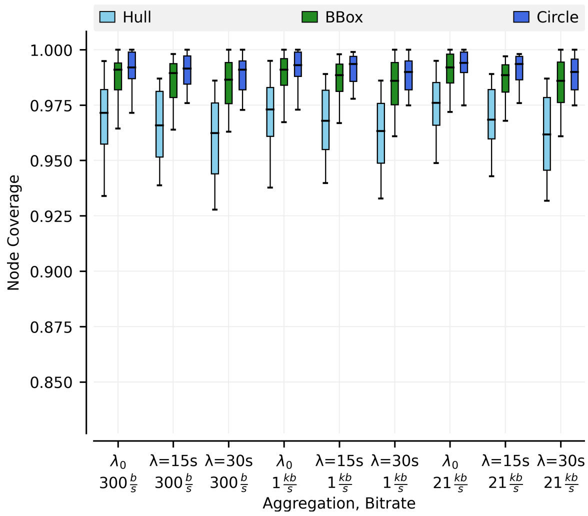
Topology Representation of Aggregations

The remaining question is, whether the aggregated information in the form of the proposed simple geometric shapes is suitable to represent the actual topology that was monitored by the UAV.

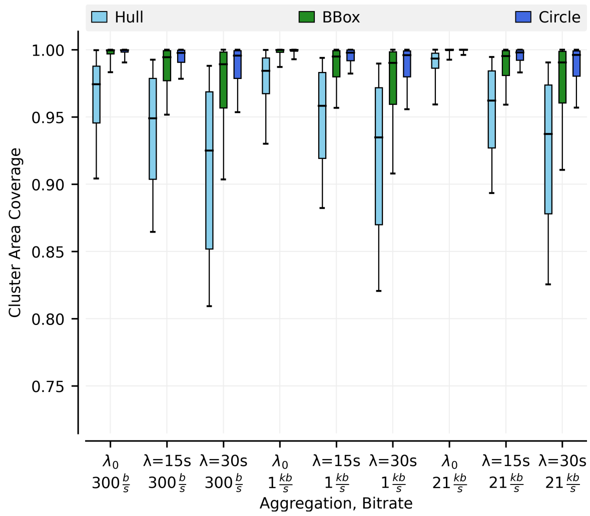
First, we look at the Age-of-Information (AoI) and the location error (LE) of the information. Both metrics encompass the difference from the initial measurement on the UAV until the final reception and assessment on the base station. Therefore, they provide a possibly expected error margin, introduced by a delayed transmission ($\lambda > 0$) and waiting times due to message queues and limited channel throughput. Figure 7 depicts results for both metrics on the example of a 1 $\frac{kbit}{s}$ bitrate. As expected, we see a direct correlation between the transmission delay λ and the AoI. However, we also see a generally larger AoI for the Convex Hull approach due to longer transmission time required as a result of the larger message sizes. Since the AoI can directly influence the location error, as it gives more time for the monitored devices on the ground to possibly relocate, the LE similarly increases with a higher delay. Nevertheless, the median LE is still zero, providing an acceptable information quality, at least within the simulated scenario. However, these results may change with other scenarios or simulated mobility models. In general, a low AoI and location error is preferable; the transmission delay should be kept as small as possible.

Second, we specifically regard the representation and accuracy of the aggregated topology information compared to the actual network topology. Figure 8 provides an overview of the used metrics. As geometric comparison baseline serves the convex hull of the network cluster at the time of receiving the aggregate at the base station. Since the Point approach does not provide an actual geometric area, no comparisons are possible.

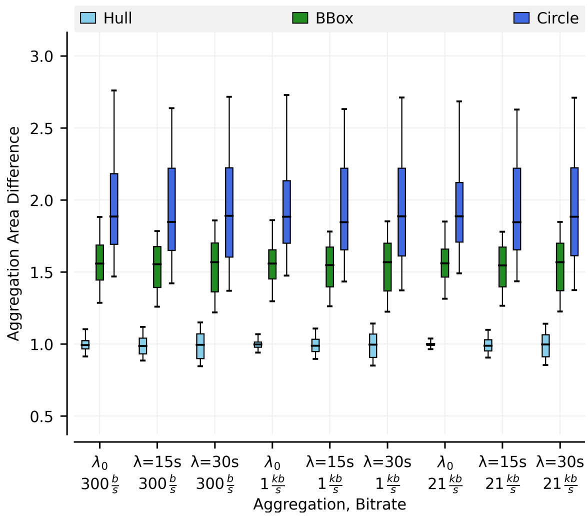
Most importantly for our approaches is, that they cover the network clusters constructed from individual nodes to represent the actual network topology. As depicted in Figure 8a, the node coverage of Convex Hull, Bounding Box, and Circle aggregates is very good, with more than 92.5% of nodes always covered. Furthermore, the less exact approaches Bounding Box and Circle usually cover more nodes than Convex Hull. This results from their larger but less precise extents, allowing more node movement on the ground before losing coverage. On the other hand, there are no significant differences on node coverage for different transmission delays. Additionally, there are only slight performance increases with a higher data rate. For the coverage of the geometric cluster representation, however, the influences of mobility in the network are much clearer. Figure 8b highlights a decrease in cluster coverage with a higher transmission delay and better coverage with higher data rate. Similar to node coverage, the less-exact Bounding Box and Circle generally cover more of the clusters, even with mobility, than the more exact Convex Hull. The tradeoff, however, becomes clear when comparing the difference in size between the aggregation and the actual network cluster (cf. Figure 8c) as well as the overlap of the aggregation with the network cluster (cf. Figure 8d), respectively. The circular aggregation area is between 1.25 and 2.75 times bigger than the actual cluster, including only 40% to 70% of it. The bounding box representation performs better, but still depicts an area up to 1.8 times the size of the actual cluster. Only the Convex Hull approach is able to closely represent the network clusters. But with a higher susceptibility to node mobility, the transmission delay also has a much larger impact on its accuracy than on the other approaches.



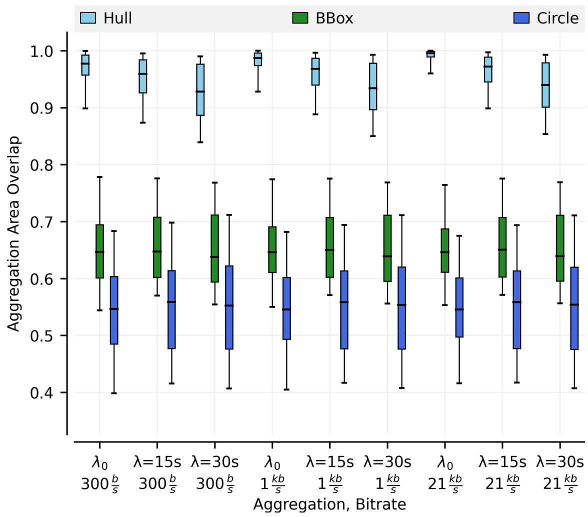
(a) Node coverage.



(b) Cluster area coverage.



(c) Aggregation vs. actual cluster size.



(d) Part of aggregation overlapping with actual cluster.

Figure 8. Overview of comparing metrics for the representation of aggregated topology information and the actual network topology and network clusters on the ground. Note that the y-axes are not starting at zero. For comparisons with the actual cluster area, the convex hull of the network cluster is used.

CONCLUSION

The possible impact and the necessary requirements of a data channel between Unmanned Aerial Vehicles (UAVs) and their operating base station is one of the less-researched topics in the field of Unmanned Aerial Systems. Especially for low-cost off-the-shelf UAVs without proper network interfaces, such as for satellite or cellular networks, alternatives are required to allow their application in large-scale disaster areas, where a central ICT infrastructure may not be available.

This paper discusses the importance of such a data channel on the example of an Aerial Monitoring System, that searches and monitors mobile devices in a disaster scenario with UAVs. This information is highly valuable, for example, to rescue services, but may arrive only with severe delay without a proper data channel available to the monitoring UAVs. LoRa is one of the suitable wireless communication technologies that could be integrated and used on off-the-shelf UAVs and we are currently working on a possible hardware implementation. LoRa provides a very robust, but also very limited low-throughput communication channel. We have shown that the bitrates achieved by LoRa are not suitable to transfer typical topology information monitored by UAVs. Therefore, we propose to aggregate topology information as simple geometric shapes, which can be transmitted using only small, basic information like a few locations or numerical values. Our evaluation results demonstrate that theses aggregations significantly reduce the size of messages for transmission to the base station. At the same time, they maintain an adequate representation of the monitored clusters and the network topology. The aggregated monitoring information can be transferred with reasonable delay and reliability towards the base station even over low-throughput networks, tested in this paper with a bitrate as small as 300 $\frac{bit}{s}$. A higher throughput reduces transmission times and message drops, further increasing the usability of both our approach and the gathered monitoring information.

Future work must encompass more realistic representations of the data channels. In this work, we focused on the application of information aggregation and its usability within limited data channels, but neglected signal losses, packet collisions, and more. Furthermore, an increase of devices in the disaster network and multiple monitoring UAVs working in parallel may further burden the used data channel, reducing its usability and effective throughput. More sophisticated, possibly situation-adaptive aggregation approaches are, therefore, necessary in combination with larger and more complex network environments. Similarly, the reduction of transmission data could be approached as an optimization problem, where only the optimal subset of actual location measurements is sent to reduce channel utilization. Nevertheless, the work in this paper provides a foundation for future research in an important, but currently unattended and not well-researched subject of Unmanned Aerial Systems.

ACKNOWLEDGMENT

This work has been funded by the LOEWE initiative (Hessen, Germany) within the *emergenCITY* center and the German Research Foundation (DFG) within the Collaborative Research Center (CRC) 1053 MAKI.

REFERENCES

Álvarez, F., Almon, L., Lieser, P., Meuser, T., Dylla, Y., Richerzhagen, B., Hollick, M., & Steinmetz, R. (2018). Conducting a Large-Scale Field Test of a Smartphone-Based Communication Network for Emergency Response. *Proceedings of the 13th Workshop on Challenged Networks*, 3–10.

Arafat, M. Y., & Moh, S. (2021). Bio-Inspired Approaches for Energy-Efficient Localization and Clustering in UAV Networks for Monitoring Wildfires in Remote Areas. *IEEE Access*, *9*, 18649–18669.

Baumgärtner, L., Kohlbrecher, S., Euler, J., Ritter, T., Stute, M., Meurisch, C., Mühlhäuser, M., Hollick, M., von Stryk, O., & Freisleben, B. (2017). Emergency Communication in Challenged Environments via Unmanned Ground and Aerial Vehicles. *Proceedings of the Global Humanitarian Technology Conference (GHTC)*.

Baumgärtner, L., Lieser, P., Zobel, J., Bloessl, B., Steinmetz, R., & Mezini, M. (2020). LoRaAgent: A DTN-Based Location-Aware Communication System using LoRa. *Proceedings of the 10th IEEE Global Humanitarian Technology Conference (GHTC)*.

Bujari, A., Calafate, C. T., Cano, J.-C., Manzoni, P., Palazzi, C. E., & Ronzani, D. (2017). Flying Ad-Hoc Network Application Scenarios and Mobility Models. *SAGE Publications Sage UK International Journal of Distributed Sensor Networks*, *13*(10).

Chakraborty, A., Chai, E., Sundaresan, K., Khojastepour, A., & Rangarajan, S. (2018). SkyRAN: A Self-Organizing LTE RAN in the Sky. *Proceedings of the 14th International Conference on Emerging Networking Experiments and Technologies*, 280–292.

Choset, H., & Pignon, P. (1998). Coverage path planning: The boustrophedon cellular decomposition. *Field and service robotics*, 203–209.

Esrafilian, O., Gangula, R., & Gesbert, D. (2020). Autonomous uav-aided mesh wireless networks. *Proceedings of the 2020 IEEE Conference on Computer Communications Workshops*, 634–640.

European Telecommunications Standards Institute (ETSI). (2018). ETSI EN 300 220-2: Short Range Devices (SRD) operating in the frequency range 25 MHz to 1000 MHz; Part 2: Harmonised Standard for access to radio spectrum for non specific radio equipment.

Fehling-Kaschek, M., Miller, N., Haab, G., Faist, K., Stolz, A., Häring, I., Neri, A., Celozzi, G., Sanchez, J., & Valera, J. (2020). Risk and Resilience Assessment and Improvement in the TeleCommunication Industry. *Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference (PSAM15).*

Gallucci, M. (2018). Rebuilding Puerto Rico's Power Grid: The Inside Story. *IEEE Spectrum*, *55*(5), 30–38.

German Federal Agency for Civic Education. (2021). Jahrhunderthochwasser 2021 in Deutschland (translation: Flood of the Century 2021 in Germany), (online) https://www.bpb.de/politik/hintergrund-aktuell/337277/jahrhunderthochwasser-2021-in-deutschland, last accessed: 20.12.2023.

Ghazali, M. H. M., Teoh, K., & Rahiman, W. (2021). A systematic review of real-time deployments of uav-based lora communication network. *IEEE Access*, *9*, 124817–124830. https://doi.org/10.1109/ACCESS.2021.3110872

Gupta, L., Jain, R., & Vaszkun, G. (2016). Survey of Important Issues in UAV Communication Networks. *IEEE Communications Surveys & Tutorials*, *18*(2), 1123–1152.

Gupta, M., & Varma, S. (2021). Metaheuristic-Based Optimal 3D Positioning of UAVs Forming Aerial Mesh Network to Provide Emergency Communication Services. *Wiley Online Library IET Communications*, *15*(10), 1297–1314.

Hagar, C. (2015). Crisis informatics. In *Encyclopedia of Information Science and Technology, Third Edition* (pp. 1350–1358). IGI Global.

Hollick, M., Hofmeister, A., Engels, J. I., Freisleben, B., Hornung, G., Klein, A., Knodt, M., Lorenz, I., Lieser, P., Mühlhäuser, M., Pelz, P., et al. (2019). EmergenCity: A Paradigm Shift Towards Resilient Digital Cities. *Proceeding of the World Congress on Resilience, Reliability and Asset Management (WCRRAM)*, 383–406.

Khelil, A., Marrón, P. J., Becker, C., & Rothermel, K. (2007). Hypergossiping: A Generalized Broadcast Strategy for Mobile Ad Hoc Networks. *Elsevier Ad Hoc Networks*, *5*(5), 531–546.

Kreienkamp, F., Philip, S. Y., Tradowsky, J. S., Kew, S. F., Lorenz, P., Arrighi, J., Belleflamme, A., Bettmann, T., Caluwaerts, S., Chan, S. C., et al. (2021). Rapid Attribution of Heavy Rainfall Events Leading to the Severe Flooding in Western Europe during July 2021. *World Weather Attribution*.

Lieser, P., Zobel, J., Richerzhagen, B., & Steinmetz, R. (2019). Simulation Platform for Unmanned Aerial Systems in Emergency Ad Hoc Networks. *Proceedings of the 16th International Conference on Information Systems for Crisis Response and Management (ISCRAM), awarded with the Best Student Paper Award*.

Mahoro Ntwari, D., Gutierrez-Reina, D., Toral Marín, S. L., & Tawfik, H. (2021). Time Efficient Unmanned Aircraft Systems Deployment in Disaster Scenarios Using Clustering Methods and a Set Cover Approach. *MDPI Electronics*, *10*(4), 422.

Moradi, M., Sundaresan, K., Chai, E., Rangarajan, S., & Mao, M. Z. (2018). Skycore: Moving core to the edge for untethered and reliable uav-based lte networks. *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking*, 35–49.

Mori, A., Okada, H., Kobayashi, K., Katayama, M., & Mase, K. (2015). Construction of a Node-Combined Wireless Network for Large-Scale Disasters. *Proceedings of the 12th Annual IEEE Consumer Communications and Networking Conference (CCNC)*, 219–224.

Mozaffari, M., Saad, W., Bennis, M., & Debbah, M. (2017). Wireless Communication Using Unmanned Aerial Vehicles (UAVs): Optimal Transport Theory for Hover Time Optimization. *IEEE Transactions on Wireless Communications*, *16*(12), 8052–8066.

Mühlhäuser, M. (2021). Panel: Resilience in Urban and Critical Infrastructures — The Role of Pervasive Computing. *Proceedings of the IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 1–2.

Ranghieri, F., & Ishiwatari, M. (2014). *Learning from MegaDisasters: Lessons from the Great East Japan Earthquake*. World Bank.

Richerzhagen, B., Stingl, D., Rückert, J., & Steinmetz, R. (2015). Simonstrator: Simulation and Prototyping Platform for Distributed Mobile Applications. *EAI International Conference on Simulation Tools and Techniques (SIMUTOOLS)*, 1–6.

Rubina, A., Artemenko, A., & Mitschele-Thiel, A. (2019). Towards a Realistic Path Planning Evaluation Model for Micro Aerial Vehicle-Assisted Localization of Wi-Fi Nodes. *Proceedings of the 44th IEEE Conference on Local Computer Networks (LCN)*, 169–176.

Saraereh, O. A., Alsaraira, A., Khan, I., & Uthansakul, P. (2020). Performance evaluation of uav-enabled lora networks for disaster management applications. *Sensors*, *20*(8).

Toya, H., & Skidmore, M. (2018). Cellular Telephones and Natural Disaster Vulnerability. *MDPI Sustainability*, *10*(9), 2970.

Université Catholique de Louvain (UCL). (2022). EM-DAT: The Emergency Events Database.

Whittaker, J., Haynes, K., Handmer, J., & McLennan, J. (2013). Community Safety During the 2009 Australian 'Black Saturday' Bushfires: An Analysis of Household Preparedness and Response. *CSIRO International Journal of Wildland Fire*, *22*(6), 841–849.

Zeng, Y., & Zhang, R. (2017). Energy-Efficient UAV Communication with Trajectory Optimization. *IEEE Transactions on Wireless Communications*, *16*(6), 3747–3760.

Zeng, Y., Wu, Q., & Zhang, R. (2019). Accessing From the Sky: A Tutorial on UAV Communications for 5G and Beyond. *Proceedings of the IEEE*, *107*(12), 2327–2375.

Zobel, J., Kundel, R., & Steinmetz, R. (2022). CAMON: Aerial-Ground Cooperation System for Disaster Network Detection. *Proceedings of the 19th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*.

Zobel, J., Lieser, P., Drescher, B., Freisleben, B., & Steinmetz, R. (2019). Optimizing Inter-Cluster Flights of Post-Disaster Communication Support UAVs. *Proceedings of the 44th IEEE Conference on Local Computer Networks (LCN)*.

Zobel, J., Lieser, P., Meuser, T., Baumgärtner, L., Mezini, M., & Steinmetz, R. (2021). Modeling Civilian Mobility in Large-Scale Disasters. *Proceedings of the 18th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*.

Zorrilla, C. D. (2017). The View from Puerto Rico – Hurricane Maria and its Aftermath. *New England Journal of Medicine*, *377*(19), 1801–1803.