

Vodafone Beyond Visual Line of Sight Drone Trial Report

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1 Executive summary

In the first trial of its kind in Europe, Vodafone has successfully demonstrated that drones - adapted to use a SIM card and 4G modem for connectivity and identification - can be remotely controlled and monitored using prototype unmanned aircraft system traffic management (UTM) technology without any additional network optimisation.

In the trial, all communications from and to the drones relied on Vodafone Germany's mobile network, using SIM cards for drone identification. Additionally, we applied Vodafone's Radio Positioning System (RPS) geo-location technology to the drone UTM scenario. RPS complements the use of GPS, which is already established as a tried and tested way of locating drones.

During the trial, held at a Vodafone testing centre in Aldenhoven, two different models of drone were flown, each carrying a SIM card that enabled separate identification and tracking. A stable, ubiquitous 4G connection permitted telemetry communications from the drones to the control technology. In addition, it was possible to send commands and instructions from the control technology to the drone (i.e. flight plans). At the same time HD video from the drones' embedded cameras was also being streamed in real time over the mobile network. Details on how the mobile network was able to facilitate these services are described in this report.

The trials demonstrated that cellular coverage improves with increasing height. Hence, even with our current mobile network design optimised for devices on the ground, the drone was easily able to maintain continuous communication with the 4G network for monitoring, control and uninterrupted HD video streaming.

Using non-cooperative methods to accurately locate a drone flying outside its registered flight plan is a serious problem for regulators that has proven difficult to overcome. It is one of the biggest impediments preventing Beyond Visual Line Of Sight (BVLOS) drone services from 'taking off' in Europe. Conventional radar does not work with such small devices, and other network-based geolocation techniques are not accurate enough. There are several aspects that impact the accuracy for each location method - the average Inter Site Distance (ISD) in the area is the most important one. ISD may vary from 500 metres in a dense urban scenario up to several kilometres in a rural area. Basic methods like "Cell ID" offer accuracies closer to the ISD while Vodafone can go even lower than ISD/10, as was demonstrated during this trial.

As a delta from what was already demonstrated in previous tests, our RPS algorithm has also been extended to include the generation of a "confidence value", which estimates the accuracy of the position estimate based on factors known to the algorithm. This report describes the results of the first trial of this new confidence value. It shows that the confidence value estimate is correlated with the true error (estimated from GPS reports). Ongoing research will focus on understanding and then compensating for any systematic error biases to improve the confidence value estimate. This will be a key feature of any network-based geo-location service offered to UTM operators, allowing them to objectively compare the accuracy of RPS location estimates with those reported by the drone itself, and detect when the drone's own GPS location reports appear to be being spoofed (indicating that it might be under malicious control and heading off its flight path).

Cellular networks will require further optimisation to support mass drone deployment, as a reliable service will have to be provided to all users. Although signal levels increase with height, measurements have shown that interference both to and from surrounding cell sites also increases as propagation to those sites improves. The net result is that 4G network quality could degrade when supporting large numbers of drones.



However, this effect will not be an issue for initial deployments of 4G connected drones supporting high-value enterprise use cases, such as drone deliveries, as initial numbers will be low and operations will usually take place in rural areas with low population densities. With the arrival of 5G, capacity will not be an issue anymore.

In order to carry out the trial, Vodafone Germany obtained an exemption under the German Regulation for the Operation of Unmanned Aircraft Systems [1], allowing BVLOS flight, which was granted by the applicable regional air traffic authority, Bezirksregierung Düsseldorf.

Vodafone is currently scoping out two further trials, in collaboration with the European Aviation Safety Agency (EASA), as part of this programme of work. We will keep working to achieve our goal of efficiently supporting connected drones to support the European Commission's U-Space vision, while maintaining the current high standards of customer experience at ground level. Guaranteeing different level of reliable services at drone heights and dealing with capacity needs will be a priority. The accuracy of the RPS algorithm will also be improved via ongoing trials so that it is considered a reliable source of geo-location information that can be used by drone traffic control authorities to verify the validity of drone GPS reports (confirming that GPS information coming from the drone can be trusted, or when GPS is not available, offering a trustable alternative).



2 Introduction and Background

Unmanned Aircraft (UA), or drone, technology has evolved rapidly over recent years resulting in corresponding cost reductions and leading many enterprises to consider how UAs might be used to support their own operations. Examples of the enterprise use cases being considered include:

- **inspection and survey** particularly towers and linear assets, such as power lines or pipelines;
- transport and logistics using UAs for the rapid delivery of small, high-value payloads to hard to access places;
- surveillance and monitoring for the detection of specific events, such as a fire or a security breach;
- communications and media such as news gathering, filming and improving cellular coverage; and
- **disaster response** for rapid information gathering and providing connectivity when conventional infrastructure is damaged.

In their simplest form, some of these use cases can be supported by "off the shelf drones", where the UA is controlled via a standard ground control system (GCS) connected using a short range point-to-point communications link, and video being streamed over a separate short range link. But such use cases are limited to Visual Line Of Sight (VLOS) operation, where the UA operations team must be present on-site and maintain visual contact with the UA at all times. This limits the range of the UA to a few hundred metres. In addition, any data collected by the drone can only be analysed locally and not in real-time at a central operations centre.

We believe that the true potential for UA support of enterprise use cases can only be realised by beyond VLOS (BVLOS) operation of UAs, and that the full requirements for safe and secure BVLOS operation can only be met by cellular connected UAs. Such UAs can be remotely monitored and controlled from a central location, with any telemetry collected by the drone (such as the video feed) or from other sources (such as weather forecasts) being analysed in real-time and the UA mission plan altered accordingly. Examples of enterprise use cases that would be enabled by cellular connected UAs include:

- **linear asset inspection** where a UA flies along the route of infrastructure, such as a power line, pipeline or railway line, looking for defects or potential hazards. Remote real-time analysis of the telemetry allows for the UA mission plan to be altered dynamically should a more detailed inspection by required. Time stamped and location tagged video can be stored and analysed automatically looking for signs of gradual deterioration, allowing for preventative maintenance to be scheduled;
- **drone deliveries** where BVLOS flying is inherent to the use case, as otherwise the pilot themselves could deliver the payload if they were anyway obliged to follow the UA using road transport. Cellular connectivity ensures that the UA and payload can be monitored until delivery is made, successful delivery can be confirmed and, should priorities change or a delivery need to be cancelled, the flight plan can be dynamically altered whilst the UA is en-route; and
- **remote surveillance** where multiple cellular-connected UAs can stream video back to a central control room for monitoring, with centralised artificial intelligence image processing used to automatically detect threats and generate alerts, and remote camera and UA position control allowing for identified threats to be investigated more closely.

To co-ordinate UA flights, and to prevent unauthorised intrusions into restricted airspace, the concept of **UA System Traffic Management (UTM)** is being investigated by regulators and would provide an automatic system for identifying UAs, approving or modifying their flight plans, and raising alerts if deviations from the flight plan were detected. We believe that cellular connectivity is key to making UTM work, not only for securely communicating with the UA, but also for UA identity verification and independent verification of its location.



Our vision is to be the communications service provider (CSP) of choice for both enterprise customers and national UTM systems in our operating markets.

To this end, we have been undertaking our own connected UA trials to demonstrate that:

- cellular networks can provide continuous high-quality coverage to UAs, despite being optimised for ground-based users;
- our 4G networks can support continuous connectivity to the UA, allowing for uninterrupted telemetry and video streaming, without significant impact on other users;
- UAs can be controlled via the cellular network, allowing both for modifications in flight plans and, if necessary, direct control of the drone;
- cellular networks can be used to identify and distinguish between different UAs; and
- our networks can estimate the location of the UA independently of GPS telemetry, thus providing a means to verify such telemetry and flag up cases where the GPS location may be being spoofed.

Some of these trials have been already reported publically (see, for example, [5] and [6]), and were brought to the attention of EASA which has responsibility for UA regulation within Europe. EASA is interested in evaluating the potential of different technologies, including mobile, to deliver safe and secure access to airspace with cost-effective and scalable U-Space services coherent with over-arching EU Transport Policy Objectives. So we expanded the scope of previous trials to include:

- simultaneous communication with and identification of multiple UAs;
- geo-location of multiple UAs simultaneously, with associated error confidence values; and
- simultaneous BVLOS control of UAs via the cellular network.

To those ends, a new trial was organised to take place at Vodafone Germany's 5G test facility at Aldenhoven, which is close to EASA's headquarters in Cologne. This document presents the results of that trial.



3 Trial Scope

This report describes "Phase 1" of the trials discussed with EASA (the first of a set of three). It gives a detailed analysis of the results from the trial and provides recommendations and next steps.

The aim of the trial was to demonstrate how a 4G mobile network can identify, monitor, track and control drones, and prove RPS is an alternative to GPS that will allow the geo-location of drones flying BVLOS without their collaboration. An additional goal was to provide information that enhances the understanding of how mobile network performance varies with height.

In order to give a flavour of how the mobile network can be used to support drone operations, a prototype of UTM technology able to manage multiple drones at the same time was developed for the trial. The technology can display information on the quality of the mobile connection plus the reported GPS location, estimated RPS location and the accuracy confidence value simultaneously for both of the drones used for the trial in real time.



4 Trial Location

The testing was undertaken at Vodafone's Aldenhoven Testing Centre (ATC) [2].

A map of the test area with the identified test locations is shown below. Permission to fly was requested within a 1 x 3 km area, which was then sub-divided in three "mission" areas to make the flight plans more manageable:



Figure 1. Missions

The ATC is surrounded by LTE 800MHz sites with an inter-site distance of approximately 6km, which allowed the trial to be conducted within the defined test area with continuous 4G coverage:



Figure 2. L800 sites surrounding Aldenhoven

The frequency band used for these nodes was in the 800MHz band with an available bandwidth of 10MHz. This band will be referred to in this report interchangeably as either 'Band 20' sites or 'L800'.



Drones were flown at constant 100m above ground level (AGL), with the ground level itself being approximately 120m above sea level (ASL):



Figure 3. Altitude ASL



5 Equipment used

The following test equipment was used during the trial:

- MiniTalon drone.
- DJI S1000 drone.
- X3 smartphone (BQ U2&X) used as access point and to give the drones connectivity.
- XCAL Mobile device with preconfigured scenarios.
- Laptops x2 to receive telemetry (1 laptop per drone).
- VF Germany SIMs for RPS tests & VF UK SIMs for throughput tests.

5.1 Drones

The drones used for the trial were two MiniTalon (fixed wing) drones [3] and two DJI S1000 [4]. The drones were modified to use cellular connectivity by fitting a smartphone as described in Section 5.2.



Figure 4. MiniTalon



Figure 5. DJIS1000



Common equipment

Part	Model	Product Code	Qty
RC Transmitter	FrSky Horus X12S	X12S-plata	2
Tx radio link	Dragon Link V3 slim		2

S1000

Part	Model	Product Code	Qty
Frame	DJI S1000+ Frame	S1000+	2
BEC	Matek System UBEC Duo	U4A2P	2
PSU	2X Pixhawk Power Module	HX4-06008	4
Autopilot	Pixhawk 2.1	HX4-06021	2
GPS	Rc Innovation	HX4-06022	2
Computer	RasberryPi 3	2525226	2
Camera	Logitech C920	960-001055	2
Rx radio link	Dragon Link V3 slim		2
Gimbal	Mini 3D PRO	9276000021-0	2

MiniTalon

Part	Model	Product Code	Qty
Frame	X-uav Mini Talon	983331	2
Propeller	CAMCarbon 10x8	723432	2
ADS + Pitot	mRo Next-Gen MS5525 Airspeed Sensor	MRO-MS5525V2-MR	2
PSU	AUAV Power Module (ACSP5) 10S-LIPO	AUAV-ACSP5-MR	2



Servos	Hi tech Hs65HB	33065S	8
ESC	Castle Phoenix Edge 50	010-0102-00	2
Motor	SunnySky X2216	X221612	2
Autopilot	mRo PixRacer R14	AUAV-PXRCR-R14-MR	2
GPS	mRo GPS u-Blox Neo-M8N	GPS002-MR	2
Computer	RasberryPi 3	2525226	2
Rx radio link	Dragon Link V3 slim		2
Camera	RPI 8MP Camera Board	2510728	2

Table 1. Equipment

5.2 Test devices

The smartphones provided continuous 4G connectivity to the drone and the Raspberry Pi via Wi-Fi tethering (smartphone offering mobile hotspot tethering capability, therefore drone connectivity was entirely relying on the mobile network). The 4G parameters required for RPS database construction were also retrieved from this device via AT commands (a programming language).

Device	Number Available	SIM Source	Specialist Test Software	Comments
BQ Aquarius X	1	VF-DE	None	
BQ Aquarius U2	2	VF-DE	None	Locked to L800
Sony Xperia XZ	1	VF-UK	Accuver XCAL	

Table 2. Available Test Devices

Note that this arrangement was a prototype used just for the trials. A commercial implementation would require a proper cellular modem integrated within the electronics of the drone. Modern chipsets and system on chip (SOC) architectures provide all the necessary communication functions for a modem other than radio frequency (RF) (antenna connectors, filters, and mixers) and power management functions. This level of integration is intended to make it easier and more economical for a cellular modem designer to offer a full-featured product specifically for drones.

All test devices had Vodafone Germany SIM cards and were connected to its live 4G network. The devices were locked to 4G Band 20 for the duration of the trial. The majority of the cells in the local area used Band 20.



5.3 Raspberry Pi

The front side of the drone has been adapted to host a Raspberry Pi 3 (Model B) inside. The board is connected to the flight controller for collecting telemetry, control data and also provides video streaming in HD through its different interfaces. The Raspberry Pi runs a continuous python script which uses AT commands to retrieve network information from the mobile handset, which is connected via USB.



Figure 6. Raspberry Pi 3 Model B

The specifications for the Raspberry Pi 3 Model B are given in the table below:

SoC	BCM2837
CPU	Quad Cortex A53 @ 1.2Ghz.
Instruction set	ARMv8-A
GPU	400MHz VideoCore IV
RAM	1GB SDRAM
Storage	Micro-SD
Ethernet	10/100 Mbps
Wireless	802.11n / Bluetooth 4.0
Video Output	HDMI / Composite
Audio Output	HDMI / Headphone
GPIO	40

Table 3. Raspberry Pi Specifications



6 System Architecture

A complete network of linked servers was set up for the trials. Its purpose was to display a plot on the UTM client in real-time comparing the reported GPS position with the location and confidence circle estimated by RPS as the drone progressed along its route. Additional information could also be shown in real-time, such as flight plan acquisition, 4G signal level indicator and the serving cell PCI indicator.

The setup for the trial was as follows:





For the trial, drone identification was based on two factors – an identifier transmitted in-band along with the telemetry, and the destination UDP port to which the telemetry was sent (different IDs for each SIMs). Both identifiers were in use – the RPS Calculation server processing the calculations only had a single user datagram protocol (UDP) port open, and so relied on the in-band identifier, whereas the data collection server, running on AWS a separate port was open for each drone.

Again, note that this was the setup for the trial. In a real commercial scenario, the system would differentiate users just by SIM card (details on routing based on ports or other internal IDs would be associated to the specific SIM profile, stored in the HSS). Placing SIMs in commercial drones will provide them with unique identifiers that can be linked to a specific owner or drone operator. The SIM provides an additional layer of hardware and software security with proven protocols, and additional encryption can be applied to all communications over a mobile network according to the user's requirements. For a **commercial setup**, RPS would be implemented as below:



Figure 8. Commercial setup



RPS could be implemented in a virtualised platform or vendor server located on the network side:

- **ingestion module** collecting real-time traces from the network operations support system (eNodeB, RNC, MME);
- **RPS module** post-processes the traces creating and storing the Fingerprint Database and applying RPS algorithm to locate users; and
- **output module** offering real-time massive location of every single radio measurement received to any platform requiring it (i.e. a drone traffic control centre).

Below is a functional description of the most important elements of the set-up used for the trial.

6.1 Drone

The drone collects information related to telemetry, control and video by using several sensors connected to its flight controller. This information is sent to the Ground Control Station through a 4G connection provided by a commercial smartphone placed within the fuselage compartment of the drone. Additionally, a radio link between the UA and the Ground Control Station has been defined to ensure connectivity between the drone and the flight operator in case the primary radio link fails. This link is also used for manual control (i.e. taking off and landing) where the 4G link is still active but manual intervention is required.

A Raspberry Pi is embedded in the front side of the drone, which is connected to the 4G handset and the flight controller to retrieve information from both sources. A continuously running Python script on the Raspberry Pi executes AT commands on the 4G device to obtain the following network information:

- Serving Cell: Cell ID, EARFCN, PCI and Reference Signal Received Power (RSRP)
- Neighbour Cells: EARFCN, PCI and RSRP

These parameters are required to build the RPS database.

The script also collects GPS information from the flight controller of the drone (latitude, longitude and altitude). Once network and GPS information is collected, the Raspberry Pi mounted on the drone sends it to our RPS Calculation and Data Collection servers using a 4G connection.

6.2 GCS

The GCS is a software application running on a computer that communicates with the drone using the Vodafone 4G network as the primary link. It displays real-time data about the drone's flight and can also be used to control it during the flight. The laptop used to host the GCS was also used to monitor the live video streamed from the drone's camera.

6.3 Servers

RPS Calculation Server

This server processes the telemetry sent by the mobile phone placed inside the drone. This telemetry includes the drone's GPS co-ordinates as well as data about the 4G network at the drone's current location, all of which are used to construct the RPS database. This is a pre-requisite to being able to estimate the drone location without use of the GPS telemetry sent by the drone.



Once the database has been created, this server is able to provide a near-real time estimation of the position of the drone based only on mobile network information. For the trial configuration, the overall processing delay in estimating the location of the drone was around 8 seconds. The algorithm also estimates the error standard deviation for a given geo-location estimate, which is used as the confidence value.

The location estimate, as well as other 4G parameters (i.e. serving PCI, serving EARFCN and serving RSRP) are then forwarded to the server.

Data Collection Server

This server synchronises the information received from the drone and RPS Calculation Server to construct a database that the UTM client uses to display real and estimated positions, as well as other 4G network parameters.

6.4 UTM Client

The main function of the UTM Client software is to display information about the drones in flight from the different telemetry sources. For example, it displays the drone's location (from its GPS reports), the estimated RPS location and confidence circle, and information about the quality of the 4G network. This information is acquired and displayed in real time. The software also allows a high level of customisation by the user.

The main elements of the interface main window are highlighted in Figure 4 and listed below:

- **map** the map is the main displaying element. Inside the map, trajectories from all the sources (GPS, Vodafone and flight plan) are displayed, along with the safety areas;
- **altitude chart** the GPS reported altitude in metres is displayed against time in minutes, showing the flight profile;
- **start button** this button activates the live data acquisition for the GPS and Vodafone data;
- GPS status this indicator shows the current GPS coverage;
- **4G data** live information about the 4G network including coverage data, serving PCI and frequency band; and
- **confidence area** confidence value, in metres, is sent from RPS Calculation Server. The value is read by the Data Collection Server, and in turn read by the client and drawn as a semi-transparent orange circle around the last received location estimation.





Figure 9. UTM Client interface



7 RPS & Confidence value

7.1 RPS - Radio Positioning System

RPS is Vodafone's geo-location solution based on the radio fingerprinting technique. It is important to highlight that Vodafone's RPS algorithm was created as a geo-marketing tool and had been already validated at ground level, achieving an accuracy of better than 60 metres for 67% of devices, which is close to the theoretical target of the fingerprinting technique and is a significant improvement on the other enhanced Cell-ID techniques described in Appendix A. As already mentioned, the application of RPS to drone scenarios represents a good alternative when GPS is not available or cannot be trusted.

The RPS system incorporates two main elements: the Radio Fingerprint Database and the use of Ubiquitous Mobile Network Information.

Radio Fingerprint Database

The Radio Fingerprint Database is a map where the radio conditions are known across the geographic area. The database stored radio measurement reports from mobile devices, including the reported GPS position, as well as the neighbour cells detected, measure signal levels (RSCP in UMTS, RSRP in 4G) and also timing information (round trip time, User Equipment Rx-Tx Time difference, propagation delay or timing advance, depending on the technology and the available reports).

This information will be continuously available for those drones accurately reporting their GPS coordinates (which will be the vast majority of drones), so RPS behaves as an artificial intelligence system that will keep learning and adapting itself to any changes in the network.

Ubiquitous Mobile Network Information

The second element is the location of mobile devices using Ubiquitous Mobile Network Information. Three steps are performed as part of this element.

- **bounding** where database samples with same Cell ID as user to be located and similar timing information are pre-selected within the whole database to be post-processed, minimising the overall delay;
- **look-up** where, within the bounded samples, the algorithm looks up the ones that have similar radio characteristics (signal level) to the drone to be located; and
- **calculation** where the estimated location is calculated as the median of the latitude/longitude of those samples, together with smoothing filters, to provide the final location of the drone.

Please, see Appendix A for a detailed analysis on other drone location techniques.

7.2 Confidence value

As with any other geo-location information source, there can be a degree of uncertainty. To address this uncertainty, the confidence value estimation is currently being developed for RPS. As the majority of error sources can be considered random and uncorrelated, it is a reasonable assumption that the error process will follow a normal (or Gaussian) distribution, at least away from the tails.



This assumes that there are no systematic sources of error (such as a sparsely populated reference database) which might lead to a bias in the location estimate. Tests to date have been conducted in locations which have been well calibrated and, in such areas, the geo-location estimate is usually unbiased.

Because the geo-location estimate is bivariate (i.e. latitude and longitude), the error distribution itself is therefore assumed to be a bivariate normal process with equal standard deviation in both the latitude and longitude errors. This will be true if the drone flight direction itself can follow any axis (where this assumption does not hold - e.g. for linear corridors where drones will predominately fly along a dominant axis - this assumption will need to be modified). However, the standard deviation will vary spatially (as some locations will lend themselves to better geo-location estimates than others), and possibly also temporally. The approach taken has thus been to estimate the standard deviation of the error separately for each geo-location estimate.

Generating and displaying confidence values is therefore equivalent to estimating the error standard deviation for a given geo-location estimate and displaying a circle proportional to that estimate. In the current implementation, the scaling factor is unity – in other words, the circle displayed around the geo-location estimate has a radius of one standard deviation (1σ) , which means that for approximately 68% of location estimates, the true location will lie within the circle. Higher (or lower) confidence values can be accommodated by appropriate scaling of the estimated standard deviation.

The standard deviation itself is estimated by generating multiple geo-location estimates using different weighting factors for the reliability of the received radio measurements. If the different estimates are tightly clustered, this suggests a reliable estimate, whereas widely distributed estimates suggests an unreliable estimate. The reported geo-location estimate is the mean of the different calculated estimates, and the standard deviation is derived from the offsets between the individual estimates and the mean. This assumes that there is no systematic bias in the different estimates, which will not be completely true.

Ongoing research will focus on understanding and then compensating for any systematic error biases. New implementations of the confidence value estimation will be then tested and validated in subsequent phases.



8 Trial results

Two types of tests were performed:

- **drone management and control tests** where, using the cellular network along with UTM software, we demonstrated that a drone flying over a pre-defined route can be controlled and monitored; and
- **performance tests** which measured the quality of the connectivity to drones in flight

8.1 Drone management and control

The technical approach followed during the trial can be seen in Section 7 above.

Identification. The system was prepared to support several drones flying simultaneously. Both drones were identified and handled separately. The system was providing GPS, RPS location, and its confidence value in real time for each drone. The aim of this system was to give a flavour of how the mobile network can be used to support drone operations.

RPS location estimation (2D). The drones were geo-located in real time in a map using RPS technology, which relies solely on Vodafone's mobile network to precisely determine the location of any mobile device, without drone collaboration. In parallel, the GPS position reported by the drone was also plotted on the screen, to show the difference in accuracy between reported GPS and RPS estimated location. The estimated confidence value was plotted in the UTM client as a 1σ (68%) uncertainty circle. This value was updated with every new estimated position of the drone(s).

Calibration tests

As mentioned, Vodafone's RPS database stores the radio network information associated with a given location to build the fingerprint database. For this trial, the location was estimated in 2D (latitude and longitude), though future phases will look to extend this to include altitude. To build the database, several calibration flights were performed covering the selected test areas. During these flights, the mobile device located in the drones were continuously sending latitude, longitudinal and network information to both the RPS Calculation and the Data Collection servers. The area was surveyed primarily with the MiniTalon to build the database, along with some random flights using the S1000.

Figure 10 shows the 3km x 1 km area near to ATC covered with calibration flights:





Figure 10. Surveyed area

When the survey was finished, random flights were performed with MiniTalon to verify the database was calibrated correctly. Subsequent tests were carried out using the DJI S1000 to ensure the location estimates were still accurate for a different drone than the one that was used to calibrate the RPS database.

Database Calibration Flight Specifications:

- 3 x 1 km with 100m separation
- 100m AGL was maintained during the flights (not constant height above sea level)

Results

Self-learning artificial intelligence software is used by the RPS Calculation Server to correlate the network information reported by the drone with the fingerprint database and thus estimate the drone's location.

As explained in previous section, random flights were performed within the test area after the RPS database had been calibrated to verify the accuracy of RPS estimated locations. For these flights, the mobile device located in the drone was continuously sending network information to both the RPS Calculation and Data Collection Servers. The real GPS location of the random flights was transmitted as well in order to calculate the location estimation error, but this information was not used for the location estimation calculation itself.

The cumulative distribution functions (CDFs) of location errors for all random flights are shown below, with the results also presented separately for all MiniTalon and all DJI S1000 flights. Only samples for which the drones were flying more than 200 metres above sea level are shown in these results to exclude measurements collected when the drones were on the ground.



Figure 11. CDFs of Location Estimation Errors for Random Flights

The 67 and 95 %iles are extracted from each CDF below (~ISD/10 and below):

Scenario	Number	Location Error (metres)	
	of Samples	67 %ile	95 %ile
All Flights	37758	257	579
MiniTalon Flights	26542	301	628
DJI Flights	11216	165	338

Table 4. Summary of RPS Location Accuracy

One important finding is that it can be seen that the location accuracy for the DJI flights was better than that for the MiniTalon flights, despite the fact that the MiniTalons were used to calibrate the RPS database. This suggests that location accuracy is not strongly influenced by the devices used to calibrate the database. The reasons for the better location accuracy seen for the DJI S1000 flights was primarily because these drones flew closer to the Aldenhoven site (because of their limited range), but their slower speed is also likely to be a factor. Further analysis of this point is ongoing with extended internal tests, and as part of the scope of phase 2 trial dedicated tests will be performed to formally characterise external factors affecting RPS accuracy, such as speed of the aircraft or location of the cellular modem within the body of the drone.

Confidence value analysis:

Another important aspect of the trial was evaluation of the confidence value prediction. Recall that the confidence value is an estimate of the standard deviation of the (vector) location error, which equates to the 68 percentile location error, assuming that the error process has a normal distribution.



To evaluate the accuracy of the confidence value, the CDFs of the difference between the measured location error and the predicted confidence value were shown below. For this metric, a negative value means the confidence value was pessimistic (higher than the actual error) and a positive value means that the confidence value was optimistic.



Figure 12. CDFs of Difference between Actual Error and Predicted Confidence Value

The results show that the confidence value was pessimistic for 65% of MiniTalon location estimates and 72% of DJI location estimates, which is very close to the requirement. However, the standard deviation of the difference is quite high, at around 150 metres, suggesting only a weak correlation between the confidence value and the location error. Note that the standard deviation of the difference for the DJI is lower than that for the MiniTalon because the mean location error itself is lower. Relative to the mean location error, the standard deviation is, in fact, higher for the DJI compared to the MiniTalon, suggesting the confidence value prediction is better for the MiniTalon than for the DJI.

This can be seen from a scatter plot of location errors against confidence value predictions, which is shown below.



Figure 13. Scatter Plot of Location Estimation Errors against Predicted Confidence Values

The bias in the confidence value towards being pessimistic can be seen from the regression lines, which have a positive intercept point. This bias is higher for the MiniTalon than for the DJI, reflecting the higher location prediction error that was observed previously. More important, however, is the slope of the regression lines, which is a measure of the correlation between the two variables. A slope of unity suggests good correlation whilst slopes approaching 0 or infinity suggest poor correlation.

It can be seen that the slope of the DJI flights is lower than that for that for the MiniTalon flights, at 0.35 compared to 0.48, which suggests that the confidence value prediction is better for the MiniTalon than for the DJI. This is also reflected in a lower R² co-efficient, of 14.7% compared to 26.6%. This may be a consequence of predicting the confidence value using an algorithm trained on data from the MiniTalon calibration flights.

A linear regression curve for the combined data has better metrics than either of the underlying data sets, with a slope of 0.53 and an R² co-efficient of 31.8%. However, this is partly a reflection of the fact that a linear regression model is not the ideal model to be using for this analysis as the confidence value is not trying to predict the individual location estimation errors per se. Nonetheless, the analysis does show scope for improvement in the generation of the confidence value (which will be included within the Phase 2 trial scope).



It is also implicitly assumed in this analysis that the underlying location error distribution is constant over the whole test area, which is only approximately true. Analysis of the performance of the confidence value prediction and its spatial dependency are ongoing, along with the preparation for other approaches to be tested in the next scheduled tests, aiming to improve the behaviour of the mathematical model.

8.2 Performance test

The purpose of the field trial was to collect an array of logs during the drone flights to enable the analysis of the connected drone performance, as explained in the introduction section.

As the drones flew at approximately the same height above ground level, insufficient data was collected for a conclusive analysis on the predicted performance of any drone at any height. However, sufficient data was collected for a basic analysis to verify whether the performance would be good enough to support current use cases (command & control, streaming, etc.) for drones flying below a few hundred metres AGL. More analysis will follow from future trials to verify the key results concluded from this trial, aiming to build a coverage model at drones' heights, matching the terrestrial grid with the level of service that could be offered for drones.

Flights were performed at a constant altitude of around 100m above ground level, with the mobile device used for communications locked to band 20 (800MHz) of the commercial 4G network. The performance analysis was based on the logs collected using an XCAL equipped mobile device embedded in the DJI S1000.

The data from these flights has been clipped in time to include only data collected whilst the drone was at the intended altitude, preventing data collected before launch and during altitude transitions from influencing the statistical results. The only part where different altitudes were taken into account was for the Delta RSRP analysis.

Detected cells

The general trend is that the number of detected cells increases with altitude, due to the longer propagation distance of signals in the free space environments as altitude goes up. This was the case for both DJI and MiniTalon, where the number of cells detected on the ground was lower than in the air:

Average Measured Cell Number	D1I	MiniTalon
On the ground	3.30	2.56
In the air	7.17	6.28

Table 5. Average Number of Detected Cells

Below is a map of the different cell PCIs that the DJI was connected to during the test flights (the actual cell location information was unavailable when this report was written).





Figure 14. Serving PCI map

Signal levels

Results show that the mean RSRP, a measurement related to cellular network coverage, was higher when a mobile device was at height compared to ground level. The following table summarizes the RSRP detected by the handset embedded in the drone during the tests at height (100m AGL):

Location	Avg. Serving RSRP (dBm)	LTE Band
ATC	-86.10	Band 20 (800 MHz)



Table 6. Summary average RSRP

Figure 15. CDF/PDF Distribution of Serving Cell RSRP



RSRP Distribution over the different flights done with the DJI:



Figure 16. Serving RSRP map

The RSRP was quite stable during the flight (so serving cell changes didn't affect stability), as shown in Figure 17 below:



Figure 17. RSRP distribution over time

Those coverage levels were enough for the drone to provide a real time HD video feed throughout the flight. The throughput required for the video feed was around 2 Mbps (1080p encoded with H.264).

Video bandwidth depends on resolution and frame rate, but up to 10 Mb/s is typical for high quality video. If the video stream is used for flight navigation and situation awareness, sub-second latency is typically needed. Streaming was done using a YouTube live streaming channel.



Delta RSRP

We look now at the differences between the detected serving and neighbour RSRP. The relative strength between detected cells is an important factor for both handover algorithm performance and interference impact. Comparing the data between different altitudes also provides a good indicator of when the network starts to degrade in terms of performance to drones.

Figure 18 and Figure 19 show the distributions of the difference, measured in decibels (dB), between the serving cell RSRP and the 1st and the 2nd strongest neighbour cell RSRP detected at different altitudes but at the same instant.



Figure 18. Scatter Plot of Delta RSRP to the 1st strongest neighbour detected



Figure 19. Scatter Plot of Delta RSRP to the 2nd strongest neighbour detected

Note that negative Delta RSRP values occur when the serving cell is not the strongest cell. This can happen due to hysteresis in the handover process, whereby the neighbour cell RSRP has to exceed the serving cell RSRP before a handover will be considered. The delay in executing the handover means the difference in RSRP can continue to increase before the neighbour cell becomes the new serving cell as the drone continues to move away from the serving cell.

The following can be noted from the above figures:

- in both cases, the probability of negative delta for ground tests (0-30m) is less than 10%, but as the altitude increases, this probability increases;
- the variation in Delta RSRP with altitude is similar for both the first and second strongest neighbours in that it decreases rapidly (with negative Delta RSRP values becoming much more likely) when the drone rises from ground level up to around 30 metres AGL, but there is much less variation beyond that for higher altitudes, with similar CDFs for drones flying at between 30 and 120m AGL.
- As would be expected, low Delta RSRP values are much more likely for the first strongest neighbour cell than for the second strongest neighbour as the first neighbour RSRP is, by definition, higher than that of the second neighbour cell.

While negative Delta RSRP is not desirable in general, it can still be seen for the ground scenario, but from the graphs, it is clear that situation clearly changes above 30m AGL, leading to a more challenging scenario in terms of interference.



Throughput

In the 800MHz band, Vodafone Germany owns 10 MHz of spectrum, which can give a maximum throughput of around 75Mb/s in the downlink and 25Mb/s in the uplink. It is unusual to be able to reach this peak speed, however, as the cell capacity is shared with other users, and throughput can be reduced by many other factors. It is important to highlight that commercial SIMs were used, so resources assigned to the drones' connections were shared with Vodafone customers.

The following analysis focuses on the achievable uplink and downlink throughput to mobile devices flying at 100m AGL. No special features or optimisations were activated in the network, and the software used to measure the throughput was an XCAL mobile test device predefined with scenarios typical of device interactions with the mobile network. The server used was located in the UK, inside the Vodafone UK network, so a UK SIM card was used for the throughput test in order to reduce the latency to the server from the UK network, and thus provide more realistic results (note that all the other tests were using VF Germany SIM cards). Note that roaming service was seamless in terms of connectivity to the VF Germany network using VF UK SIM cards.

	#samples	Avg	Мах	95%-tile	BW	EARFCN
Downlink Throughput	3048	9.48 Mb/s	46.2 Mb/s	24.38 Mb/s	10 MU-	6300
Uplink Throughput	1360	15.9 Mb/s	20.9 Mb/s	19.9 Mb/s		

Below, a summary of the main results is presented:

Table 7. Summary of throughput values achieved at 100m AGL

Next, we look with more details at the achieved throughputs in both Downlink and Uplink.

Table 8 compiles main throughput DL and UL distribution:



DL throughput (Mbps)				UL throughput (Mbps)				
No.	Range	PDF	CDF	No.	Range	PDF	CDF	
1	0.00 <= x < 2.00	1.56%	1.56%	1	0.00 <= x < 2.00	1.25%	1.25%	
2	2.00 <= x < 4.00	5.87%	7.43%	2	2.00 <= x < 4.00	2.72%	3.97%	
3	4.00 <= x < 6.00	18.19%	25.62%	3	4.00 <= x < 6.00	1.99%	5.96%	
4	6.00 <= x < 8.00	18.19%	43.81%	4	6.00 <= x < 8.00	1.69%	7.65%	
5	8.00 <= x < 10.00	15.51%	59.32%	5	8.00 <= x < 10.00	3.38%	11.03%	
6	10.00 <= x < 12.00	9.19%	68.51%	6	10.00 <= x < 12.00	5.74%	16.76%	
7	12.00 <= x < 14.00	8.28%	76.79%	7	12.00 <= x < 14.00	8.24%	25.00%	
8	14.00 <= x < 16.00	7.17%	83.96%	8	14.00 <= x < 16.00	8.90%	33.90%	
9	16.00 <= x < 18.00	3.39%	87.35%	9	16.00 <= x < 18.00	21.54%	55.44%	
10	18.00 <= x < 20.00	2.22%	89.57%	10	18.00 <= x < 20.00	41.10%	96.54%	
11	20.00 <= x < 22.00	1.43%	91.00%	11	20.00 <= x < 22.00	3.46%	100.00%	
12	22.00 <= x < 24.00	1.56%	92.57%					
13	24.00 <= x < 26.00	1.63%	94.20%					
14	26.00 <= x < 28.00	1.30%	95.50%					
15	28.00 <= x < 30.00	1.50%	97.00%					
16	30.00 <= x < 32.00	1.43%	98.44%					
17	32.00 <= x < 34.00	0.52%	98.96%					
18	34.00 <= x < 36.00	0.52%	99.48%					
19	36.00 <= x < 38.00	0.33%	99.80%					
20	38.00 <= x < 40.00	0.07%	99.87%					
21	40.00 <= x < 42.00	0.07%	99.93%					
22	42.00 <= x < 44.00	0.00%	99.93%					
23	44.00 <= x < 46.00	0.00%	99.93%					
24	46.00 <= x < 48.00	0.00%	99.93%					
25	48.00 <= x < 50.00	0.07%	100.00%					
		Avg	9.48			Avg	15.9	
Max	46.2	Min	0.01	Max	20.92	Min	0.02	
STDEV	7.05	Median	8.67	STDEV	4.51	Median	17.59	

Table 8. DL/UL throughput distribution



Example of DL throughput test:



Figure 20. DL throughput over time



Figure 21.CDF/PDF Downlink throughput distribution



Figure 22. CDF/PDF Uplink throughput distribution

If we plot the samples over the route where the tests were done, it can be seen that the performance offered along the whole route is very uniform, suggesting that a 'minimum' service level can be offered to drones without doing any additional optimisation of the mobile network:



Figure 23. DL/UL throughput distribution map

Some other interesting key performance indicators, summarised in the table below, were measured:

Serving Cell RSRP [dBm]	Serving Cell RSRQ [dB]	Serving Cell RSSI [dBm]	Serving Cell SINRO [dB]	DL Mod Total QPSK Rate [%]	DL Mod Total 16QAM Rate [%]	DL Mod Total 64QAM Rate [%]	UL Mod QPSK Rate [%]	UL Mod 16QAM Rate [%]
-84.91	-13.84	-53.44	1.02	56.9	35.4	7.7	8.2	91.8

Table 9. PS Call Statistics

While higher order modulation rates are able to offer faster data rates, this comes at a price. The higher order modulation schemes are considerably less resilient to noise and interference. From the table above, it can be seen that, at heights, the radio links are not that reliable, and that is solved by reverting to a lower modulation scheme (QPSK used 56.9%).



Summary of Key Results

- The number of detected cells increases with altitude.
- The throughput performance starts to degrade above 30 metres AGL, meaning that specific network optimisation will be required in order to support connectivity at those heights for mass drone deployments.
- Without any additional optimisation of the mobile network design, the throughput achieved is still sufficient for the current services that might be used by the drones (basic connectivity from/towards a control centre for commanding and tracking). The network requirements for different types of service still need to be modelled. For example, the requirements to support simple telemetry (low throughput, medium latency) are radically different to those required for 4K real time video streaming (high throughput, low latency).



9 Conclusions and recommendations

The first and major conclusion of this trial is that the 4G mobile network can be used to identify, monitor, control and geo-locate connected drones. The current network design, which is carefully optimised for ground-level users, was found to be good enough for the general needs of drone communications, such us telemetry and command & control (10s of kbps), real-time video feeds, and application specific data transfers such as sensor measurements and images collected (1-8 Mbps). Moreover, it was confirmed that a worldwide and standardised ID, the SIM, can solve the identification problem for drones, enabling discrimination between different drones (acting like an aircraft transponder), in the same way each "ground-level" customer is uniquely identified by their operator.

The number of detected cells was found to increase with altitude due to propagation tending to free space and thus increasing received signal strengths over longer distances. Hence received signal strengths for mobile devices at altitude are strong despite down-tilted antennas in the network. In fact, the received signal strengths are typically stronger for mobile devices at altitude (below 120m) than for ground devices because the tendency to free space propagation conditions at altitude outweigh any antenna gain reductions due to down-tilted antennas. However, it was seen that throughput performance decreases at altitudes above 30m AGL. To be prepared for mass drone deployments, a number of enhancements and optimisations are being considered on the network side that will simultaneously provide services to ground and airborne UEs, optimised to meet the performance requirement of each class of device. Additionally, the construction of a coverage model at drone heights versus terrestrial grid available at any location will help us further characterise the different service levels that can be currently offered in terms of connectivity, and what is the gap to be covered with enhanced 4G techniques and new 5G capabilities.

RPS has proved itself as a valid indicator of drone location during low level BVLOS flight that is independent of GPS reports from the drone. RPS can therefore provide an independent verification of the accuracy of the GPS reports. Other network-based geo-location techniques using only radio measurement reports are not accurate enough, and high-precision network-based geo-location techniques do not justify the deployment cost (network side) or embedded hardware costs (drone side) for this use case.

The application of RPS for the drones use case is still relatively new, but the accuracy reached during the trial was better than 250m for 67% of the estimates, though this means that there is still room for improvement. The accuracy of RPS will improve in line with the number of cell sites that the drone can access. Results show that location accuracy is not strongly influenced by the devices used to calibrate the database. The reasons for the better location accuracy for the DJI drones was primarily because they flew closer to the Aldenhoven site, where the location estimation accuracy proved to be better, though the slower speed of the DJIs may also have been a factor. As already explained, further tests will be performed to formally characterise this influences. This shows that location accuracy varies with location, and a confidence value estimate was developed to provide a quality measure for the location estimates.

The confidence value will be a key feature of any network-based geo-location service offered to UTM operators, allowing them to objectively compare the accuracy of network generated location estimates with those reported by the drone itself and generate alerts when the drone-reported location appears to be being jammed or spoofed. It was shown that a location confidence value correlated with the measured error can indeed be generated by the RPS algorithm, though further development to improve the correlation and demonstrate the applicability of the approach to a wider range of environments and scenarios remains to be done.



10 Next steps

More work is still required to reach the goal of efficiently supporting mobile devices on drones flying at low altitudes whilst still maintaining excellent customer experience levels for mobile devices on the ground.

Equally, we will keep improving the artificial intelligence algorithm to improve the accuracy of RPS for estimating the location of a drone. We will continue to work on improving the confidence value model so that RPS can be a reliable as well as accurate source of geo-location information that can be used to indicate when the GPS reports from a drone are not reliable. Analysis of the performance of the confidence value prediction and any spatial dependency is already ongoing and new approaches for generating a confidence value will be tested in the near future.

It is currently expected that capabilities to be demonstrated in subsequent phase 2 and phase 3 will include:

- RPS location in 3D (including altitude) & confidence value model improvement;
- dynamic no-fly zones allocation & geo-fencing with remedial action to be taken if a drone was to enter a no-fly zone (note that specific action to be taken will depend on the capabilities of the drone);
- latency analysis between the GCU and the embedded mobile device on the drone;
- implementation of different "authority levels" when accessing location information and flight plans, so that the information available to everyone (for collision avoidance, for example) is differentiated from information available for a central control entity;
- o characterisation of different service levels and coverage modelling;
- $\circ~$ application of 4G enhanced techniques (such as Active Antennas) to maximize the quality of the connection at drone heights; and
- o 5G capabilities tests.



11 Appendix A

Available drone location techniques

There are a number of different location techniques based on information that originates from the mobile network, namely Cell ID, Triangulation/Trilateration, Observed Time Difference of Arrival (OTDOA)/Uplink-Time Difference of Arrival (UTDOA) and Fingerprinting. These are summarised below.

Cell ID is a methodology based on correlating the measurement of the unique identifier of the radio transmitter with the known transmitter position based on network topology data. The accuracy is highly dependent on the coverage of the transmitter (average ISD); the lower the range of the transmitter, the higher the accuracy. Accuracy can go from 250m up to several kilometres.

Triangulation/Trilateration uses simultaneous User Equipment (UE) measurements from different transmitters and correlates them geographically. The technique estimates distance between the UE and each transmitter from coverage (propagation models) or timing measurements (Round Trip Time - RTT). The accuracy of this technology depends on the number of simultaneous reported transmitters as well as on the receiver-transmitter distance. The higher the number of reported transmitters, the smaller the intersection area and the better the accuracy. Accuracy can reach up to 100m in dense urban areas.

OTDOA/UTDOA is a methodology is based on the measurement of the time difference between the UE and multiple base stations synchronized by GPS. Accuracy can be about <50m if clock accuracy is <50 nanoseconds. A current challenge is that networks in Europe are not yet widely synchronised by GPS and once they are (required for example for 5G), the clock accuracy could go up to 1.5 microseconds, impacting the accuracy significantly (>100m).

The main constraint of GPS measurement data is that not all devices have GPS available and in some indoor scenarios there is no satellite coverage. To address this, **Radio Fingerprinting** is a method that geo-locates users/devices without GPS by taking advantage of other UEs sending GPS measurements positions along with RF measurements. Accuracy is up to 50m in dense urban areas.

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13 Acronyms, abbreviations, and terms

Α

AGL Above Ground Level · 10, 23, 28, 31, 32, 36, 37 ATC Aldenhoven Testing Centre · 10, 22, 28, 29 AWS Amazon Web Server · 16

B

BVLOS Beyond Visual Line Of Sight · 37 BW Bandwidth · 32

С

CDF

Cumulative Distribution Function · 23, 24, 25, 33, 34, 35 Cell ID Cell Identifier · 17, 20, 39

D

dB decibel · 35 DL Downlink · 32, 33, 34, 35

Ε

EARFCN

E-UTRA Absolute Radio Frequency Channel Number · 17, 18, 32

G

GCS Ground Control Station · 17 GCU Ground Control Unit · 38 GPS Global Positioning System · 9, 13, 14, 16, 17, 18, 20, 22, 23, 37, 39

Η

HD High Definition · 5, 15, 29 HSS Home Subscriber Server · 16

L

LTE

Long Term Evolution · 6, 10, 14, 16, 17, 18, 20, 27, 28

М

MME Mobility Management Entity · 17

0

OTDOA Observed Time Difference of Arrival · 39

Ρ

PCI Primay Cell Indicator · 16, 17, 18, 28 PDF Probability Density Function · 33, 34, 35 PoC Proof of Concept · 14, 16 PS Packet Switch · 35

R

RF Radio Frequency · 14, 39 RNC Radio Network Controller · 17 RPS Radio Positioning System · 6, 9, 14, 16, 17, 20, 22, 23, 24, 37, 38 RSCP Received Signal Code Power · 20 RSRP



Reference Signal Received Power · 17, 18, 20, 27, 28, 29, 30, 31, 35 RSRQ Reference Signal Received Quality · 35 RSSI Received Signal Strength Indicator · 35 RTT Round Trip Time · 20, 39

5

SINRO Signal to Interference & Noise Ratio · 35 SoC System on Chip · 15

U

UAV Unmanned Aerial Vehicle · 17 UE User Equipment · 6, 14, 17, 20, 32, 37, 39 UK United Kingdom · 14, 32 UL Uplink · 32, 33, 35 UTDOA Uplink Time Difference of Arrival · 39 UTM UAS Traffic Management · 5, 9, 16, 18, 19, 22

V

VF

Vodafone · 4, 14