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Article

Enabling Technologies for the Navigation and Communication of UAS Operating in the Context of BVLOS

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Abstract: Unmanned Aerial Systems (UAS) have rapidly gained attraction in recent years as a promising solution to revolutionize numerous applications and meet the growing demand for efficient and timely delivery services due to their highly automated operation framework. Beyond Visual Line of Sight (BVLOS) operations, in particular, offer new means of delivering added-value services via a wide range of applications. This "plateau of productivity" holds enormous promise, but it is challenging to equip the drone with affordable technologies which support the BVLOS use case. To close this gap, this work showcases the convergence of the automotive and aviation industries to advance BVLOS aviation for UAS in a practical setting by studying a combination of Commercial Off-The-Shelf (COTS) technologies and systems. A novel risk-based approach of investigating the key technological components, architectures, algorithms, and protocols is proposed that facilitate highly reliable and autonomous BVLOS operations, aiming to enhance the alignment between market and operational needs and to better identify integration requirements between the different capabilities to be developed.

Keywords: UAS; UAVs; BVLOS; communication systems; autonomous navigation

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1. Introduction

UAS are currently conquering the skies due to their autonomous capabilities, high mobility, and fast and flexible deployment. Typically, the more general term of UAS consists of the unmanned aircraft, namely Unmanned Aerial Vehicles (UAV), a Data Link, and the Remote Pilot Station (RPS) [1]. With the emergence of new technological advancements in communication and sensor technologies, these systems have gained the potential to catalyze equivalent fundamental change in our mobility infrastructure. Particularly, BVLOS operations are playing a pivotal role in unlocking the full potential of unmanned systems due to their extended intelligence and autonomy. BVLOS refers to the capability of an unmanned vehicle to operate where humans cannot reach, following a predefined route, while any onboard information is obtained using advanced sensing instrumentation, such as on-board cameras and detect and avoid technologies. In such a highly automated operation framework, the aircraft is able to conduct its own mission, make its own decisions during the mission, and react to unforeseen events without the pilot's intervention [2]. What is more, the integration of technical components and subsystems that are optimized for specific UAS applications becomes paramount. These application-optimized components capitalize on the wealth of expertise garnered from diverse domains, with a special emphasis on Electronic Components and Systems (ECS), while the the continuous technological advances in the field open the gates for more versatile applications. Indicatively, UAS can alleviate humans from exposure to hazardous environments, perform frequent and efficient inspections, provide dynamic security, ensure access to high-frequency aerial data, utilize edge computing in an efficient manner, enable rapid response during emergencies, as well as enable object building maintenance and consumer market [3,4]. Over the past few years, drone industry investments have been progressively reaching new records, while the relevant business use cases of commercial UAS have expanded significantly [5]. In addition, technology advancements in sensors and communication technologies have opened the way for new applications that will further boost their use in sectors such as agriculture, environmental monitoring, infrastructure inspection, public safety, and emergency response.

1.1. Opportunities and Challenges

BVLOS operations offer new means of delivering value-added services via a wide range of applications, ranging from remote sensing for object detection and tracking [6]; search and rescue operations; disaster and crisis management [7]; precision agriculture [8]; or environmental monitoring [9] to logistics and industrial applications such as freight transportation [10] or the delivery of medical supplies [11]. This 'plateau of productivity' holds particular promise but demands new technical and regulatory capabilities to support drone operations in long range as well as UAS operation in the future high volumes of air traffic.

Highly reliable and precise multi-technology communication systems, fail-operational hardware, and fault tolerant software are all essential requirements for the further enhancement of highly reliable and autonomous BVLOS flights for everyday tasks, like the delivery of goods. These systems must ensure accurate and safe navigation as well as dependable control links, all while maintaining a cost level that aligns with acceptable expenses for mass-market product delivery. The realization of efficient and cost-effective drone delivery applications can be facilitated by a combination of Commercial Off-The-Shelf (COTS) technologies and systems, possibly sourced from other industries. Moreover, integration with existing planning and flight management infrastructures in the concept of Urban Air Mobility (UAM) [12] and incorporating established aviation technologies such as the integration of the ADS-B (Automatic Dependent Surveillance-Broadcast) surveillance protocol ensures compatibility with existing airspace users and the safety of operations [13]. BVLOS demands levels of autonomy and collaboration that have hither to only been seen in the autonomous vehicle market. It is expected that technologies developed for those markets can be exploited for drone application. Technology must be compliant with the regulatory framework that needs to be defined. Fortunately, that process is already in flow with U-space (U-space), building and testing the operational and regulatory framework that enables this new dawn from a regulatory and compliance perspective [14].

1.2. Scope and Contributions

This paper provides an overview of the enabling technologies that play a pivotal role in advancing the field of BVLOS operations. Unlike existing literature, we provide a comprehensive coverage of recent developments in both navigation and communication technologies for UAS, identifying patterns, trends, and gaps in the existing research landscape. We explore the essential technological components, architectures, algorithms, and protocols and shed light on the critical aspects that facilitate safety and reliability in

BVLOS scenarios, while also adopting a risk-based approach. In this way, we pave the way for future endeavors to address these gaps and boost BVLOS operations towards greater efficacy, security, and success. To support the work, the Arcadia and Capella tools [15] were used to develop a drone reference logical architecture. This created an improved understanding between market and operational needs (e.g., capabilities needed to operate within the U-space [16]) and to better identify integration requirements between the different capabilities to be developed. Our motivation lies in the necessity to address current gaps and challenges in UAS navigation and communication technologies. Through the implementation of these tools, we improved our capacity to identify the integration needs between various capabilities, which paved the way for a better-coordinated and well-informed development of technologies essential to BVLOS operations. This holistic approach contributes to bridging the gap between theoretical advancements and real-world application, which eventually promotes the development of a stronger and more reliable framework for BVLOS operations going forward.

The remainder of the paper is organized as follows: Section 2 discusses various background studies related to the technological developments of UAVs. It also presents the key technologies that have been identified as key drives for safe and reliable UAS operations, as well as some emerging UAS use cases that facilitate future growth of UAS. Section 3 explains the proposed architecture and related components. Section 4 presents the implementation details of the proposed technologies that verify the performance with the existing work. Finally, a conclusion with open issues and future directions is presented, while the societal aspects and regulatory considerations that influence the wider adoptions of UAS are discussed in Section 5. Section 6 presents the conclusions of this work.

2. Related Work

Nowadays BVLOS flights open a myriad of applications revolutionizing various industries, from goods delivery to safety and security, through surveying, crowd management, as well as search and rescue [17]. Drones can make a significantly positive impact on customer satisfaction by enhancing the quality of delivery services. In recent years, many leading retail companies, such as Amazon, Google, and Walmart, were introducing drone delivery services [18]. "Amazon Prime Air" was initiated by Amazon to deliver packages of 2.3 kg within thirty minutes at a distance of 16 km from click to delivery [19]. After introducing innovative sensor technologies and communication systems to their UAS delivery services, the company aspired to reduce noise pollution, eliminate their carbon footprint, and facilitate safer and more reliable services. In 2019, DHL launched its first fully automated, intelligent drone delivery solution in China which reduces one-way delivery time from 40 min to only eight minutes and can save costs of up to 80% per delivery, with reduced energy consumption and carbon footprint compared to road transportation [20].

The key to unlock the potential of UAS, and allow various related applications to bloom, is to develop components, systems, and architectures for autonomous, intelligent, and safe UAS use, beginning from the industrial domain(s) for components, over system design and development, with cross-domain contributions to system architectures for resilience, robustness, and collaboration air-to-ground. SESAR (Single European Sky Air Traffic Management Research) has already started work on regulatory and procedural structures for drone co-existence with crewed traffic with the U-space architecture and has defined levels of implementation of that architecture U1–U4, covering the period from 2019 to 2035 [14]. In the following sections, we present some of the key technologies that have been identified as key drives for safe and reliable UAS operations.

2.1. Detect and Avoid Technologies

Detect and Avoid (DAA) technologies are key to unlocking commercially viable BVLOS operations, as they allow a safe and efficient integration into civilian airspace, by helping UAS to avoid collisions with other aircraft, buildings, and other obstacles. The growing number of UAS applications has made a necessity for sophisticated and highly dependable collision avoidance systems, as evident and incontestable from the public safety perspective [21]. Such systems are based on the use of sensors to detect and position obstacles to subsequently establish maneuvers to guarantee the safety of the aircraft. Many recent works implement LiDAR (Light Detecting And Ranging), vision cameras, or thermal or infrared cameras for collision avoidance of UAS [13,22].

The detection of possible objects in the navigation space can be also realized using pattern recognition technology, which includes methods for identifying relevant characteristic features of an object via image processing algorithms. Deep learning algorithms for object detection with high sensitivity to data restructuring are the most common approaches in object detection and classification [23].

2.2. Communication Technologies

The reliability of UAS communication technology is essential for their wider deployment. The commercialization of fifth-generation networks (5G) technology provides UAS communication with ultra-high speed, very low latency, high data rate transmissions, and other capabilities, which effectively solve the problem of the UAS communication quality [24], at least when the operational volume is within the coverage of the mobile network. However, current UAS communication systems still face several limitations in terms of UAV aerial base station (BS) deployments, spectrum utilization, and energy consumption of UAV communication [25]. Extensive research has been conducted regarding UAV groups, categories, sorting, charging, and adjustment. In the last few years, the European Telecommunications Standards Institute (ETSI) defined a new concept called "Multi-access Edge Computing" (MEC) which refers to the deployment of cloud computing services at the edge of the cellular network. UAVs can be integrated into MEC networks as users that execute various computing tasks [26]. Such systems can significantly decrease network congestion and increase the network performance in applications related to task allocation [27].

Future UAS applications have stricter demand for latency, data rates, and reliability and channel variations introduced by their mobility, which in turn relocates research interest beyond fifth-generation (B5G) mobile communications. Emerging UAS scenarios include drones that can act as mobile roadside units (RSUs), gathering data from an area and transmitting that data to terrestrial vehicles, stationary RSUs, and other nearby drones. UAS networks can be deployed faster than any other stable network infrastructure system; thus, it is better to use them as the basis of mobile infrastructure networks for remote locations [28]. To enhance network and performance in UAS communication, the existing literature has explored various emerging wireless communication technologies, such as non-orthogonal multiple access (NOMA), which prevails over the traditional orthogonal frequency-division multiple access (OFDMA) schemes due to its unique characteristics, such as enhanced spectrum efficiency (SE) and reduced traffic latency with high reliability [29].

Towards protocols for the UAV to ground control communication, only related work dealing with non-military approaches is discussed in the following. There are several protocols applicable to the commercial drone use case which can be utilized in the mobile network context. One widely used protocol is the Micro Air Vehicle Link (MAVLink) protocol, which is applicable to wireless radio communications. It is lightweight and its reliability is ensured by double checksum. Kosuda et al. [30] discuss the potential of using it for UTM communication, such as identification or traffic monitoring. One drawback is the lack of security mechanisms, such as message encryption. However, when deployed on a cellular network, the data is encrypted when sent over the wireless link by the mechanisms implemented in the mobile network [30]. Furthermore, there are other open-source and lightweight protocols, such as the UranusLink protocol and the UAVCan protocol, although they are less commonly used. Similar to MAVLink, both protocols lack security mechanisms. However, the UAVCan protocol provides limited encryption ability [31]. In contrast, our work proposes a Wireless Safety and Security Layer (WSSL), addressing the safety and security concerns.

2.3. Autonomous Navigation

Awareness of the UAS surroundings is a key aspect of BVLOS operations, particularly in large-scale and complex environments. Drone navigation is characterized by two fundamental components: path planning and obstacle detection and avoidance. Path planning involves determining an optimal trajectory for the drone and defining parameters such as the velocity and turns over time, to achieve optimality in the trajectory generation. As such, each autonomous flight is characterized by an objective, either being the arrival to a certain target point, or the aim of maximizing the information coverage [32]. With regards to UAS navigation, different path-planning alternatives can be used depending on the specific requirements of the application [33]. These methods can be classified into two categories: those that are based on a sampling of the search space, and those that employ artificial intelligence (AI) to find a solution with respect to the representation of the environment [34]. There exist various different sampling based UAS navigation techniques, for example, graph-based shortest-path-finding algorithms, such as Dijkstra's algorithm [35] and its variations [36], the A* path search algorithm [37], or the Fast Marching (FM) [38] Potential Fields [39] and Rapidly exploring Random Tree [40] methods. Genetic algorithms and other bio-inspired techniques have also been employed for UAV path planning [41]. These methods avoid constructing complex environment models and search for a near optimal path based on stochastic approaches, so they provide efficient solutions to NP-hard problems with many variables and non-linear objective functions [42]. Finally, Reinforcement learning (RL) methods allow for UAV navigation in highly dynamic environments as the aircraft is able to learn from the results of past actions and uses environmental feedback as the input for path planning. The use of DRL techniques to train neural networks through a Reinforcement Learning (RL) strategy are becoming popular in the field of UAV navigation [43].

Recent works on autonomous UAV navigation have mainly focused on the creation of a 3D map of the surrounding environment. This 3D deployment and resource utilization has been addressed by powerful optimization methods such as convex optimization [44] or game theory [45]. In addition, various path-planning methods have been deployed for obtaining optimal paths, including graph-based methods such as the A* algorithm [46,47], or evolutionary methods such as the Particle Swarm Optimization (PSO) [48,49]. The observation that UAS navigation can be treated as a sequential decision-making problem has led more and more researchers to the use of learning-based methods for solving complex navigation problems and intelligently managing onboard resources [50]. AI and ML models play a vital role to all these tasks as the main part of the processing pipeline, which begins with data collection and pre-processing and ends with inference and decision making in real time. The models for some tasks are continuously or periodically trained in order to adapt to new conditions and environments and this process can be carried out either online or offline. Recent works have implemented the Deep Reinforcement Learning (DRL) algorithm for solving UAVs' reactive navigation problems in a simulated environment [51] or in real-world conditions [52].

The Mounted Mobile Edge Computing Network (MEC) can provide more flexible and reliable UAVs' connectivity with affordable infrastructure investment. Some interesting studies focused on UAVs' path planning and obstacle avoidance in MEC networks using a DRL-based algorithm [53,54]. Additionally, UAV-supported wireless communication systems have been implemented to enhance robustness and optimize network performance via the utilization of a deep Q-network (DQN) framework [55].

Although autonomous navigation methods are continuously evolving, driven by technological advancements, BVLOS can only be successful if carried out in concert with other roadmaps for regulatory development and operating standards and procedures. Initiatives to unify European regulatory standards for commercial drone operation have been introduced by EASA and a Specific Operations Risk Assessment (SORA) can be conducted that aids safety and compliance for operations in urban environments. Moreover, if the planned operation reaches into airspace where the drone may come into contact with traditional (manned) aviation, the upcoming regulations around U-space come into play, of which it is currently being developed by SESAR [56].

2.4. UAS Emerging Use Cases

Recent technological developments, trends, and societal needs have opened the way for an unparalleled expansion in the use of UAS for a great number of applications, where humans cannot reach or are unable to perform in a timely and efficient manner. The following section presents some emerging UAS use cases.

2.4.1. Logistics and Delivery of Goods

The existing logistics domain could benefit by integrating UAS technologies to achieve a more sustainable distribution of goods. For example, package delivery, the carrying of critical medical supplies to remote or inaccessible areas, or even aerotaxis capable of carrying passengers are some of the application areas where UAS offer great potential. Overall, UAS can provide advanced features against conventional solutions in logistics services, such as simultaneous delivery at several locations, reduced operational costs, environmental benefits, reduced traffic congestion and risk for accidents within large cities, and accessibility to remote areas or areas without infrastructures [57].

2.4.2. Forestry and Agriculture

In forestry and agriculture, autonomous, intelligent, and safe systems have received substantial attention in recent years. Technological advancements are rapidly adopted and pave the way for an operational UAV-supported forest monitoring system and boost further adoption among stakeholders. What is more, UAS can be used for various agricultural activities, such as the collection of weather data, the monitoring of crop growth, the early detection of crop diseases, the prevention of crop wastage due to the effective harvesting of crops, the monitoring of livestock behavioral patterns, animal location within and outside the farms, and an increase in production for both crops and livestock with the aim to boost farm productivity [58].

2.4.3. Infrastructure Maintenance

In recent years, the introduction of UAS technology as an additional remote, non-destructive method for infrastructure inspection and maintenance is increasingly attracting interest. UAS equipped with different camera and sensor technologies may represent an efficient and cost-effective support for improving the quality of infrastructure inspections [59]. UAS can also enhance the automation of monitoring activities of the infrastructure and allows for gathering crucial data needed for decision-making policies on the maintenance, repair, retrofit, or rebuild of bridges, thus increasing the resilience of the infrastructure network. UAS can carry out these activities and also promise a quicker and more cost-effective turnaround preparation of maintenance, resulting in lower overall maintenance costs and lower impacts on the traffic that is using the superstructure [60].

2.4.4. Search and Rescue Operations

UAS offer great potential is the search and rescue domain. Beneficially envisioned and applied applications in recent years extend to forest health monitoring, fire mapping applications, forest inventory, disaster prevention, and disaster management. UAS equipped with enhanced sensory abilities and novel control systems, as well as the capability of sophisticated mapping in unknown environments, prove beneficial for operating in harsh or difficult-to-access remote areas [61].

3. Architecture and Functionalities

In this section, we present a comprehensive overview of the proposed technologies, architectures, algorithms, and protocols that are crucial for a UAS sub-system to effectively manage navigation tasks for the further enhancement of highly reliable and secure drone missions. Figure 1 depicts the overview of the technologies developed to tackle this challenge.

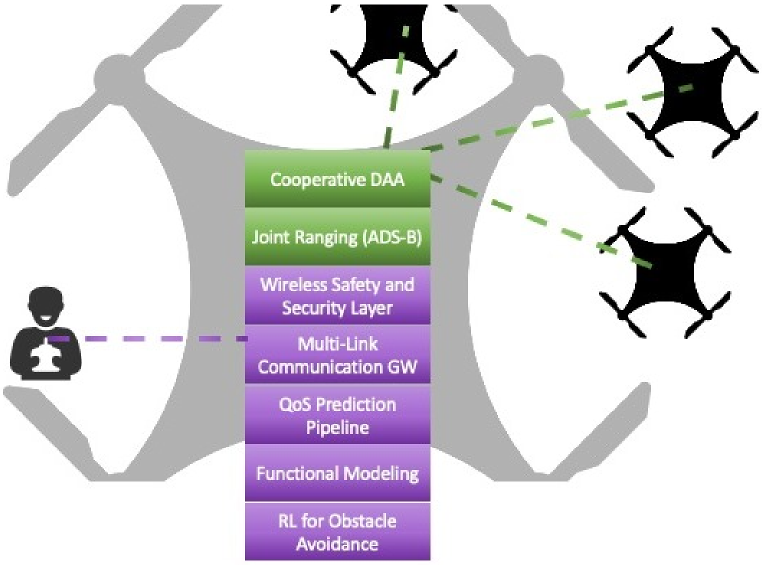

Figure 1. Overview of the developed technologies.

To build and operate UAS safely and economically, it makes sense to base the systems on available commercial technologies and services where possible. This is true for the command, control, and communication (C3) link as well. Public mobile communication networks are a prime example of this, as well as WiFi and similar technologies for more local links, or satellite links to achieve an even larger operational area. The usage of economically viable, commercial service providers or off-the-shelf technologies allows us to increase the reliability of the connection between the UAV and the operator, through redundancy via the use of multiple underlying links for the C3 link.

Compared to the technologies used in traditional aviation, commercial mass market communication technologies evolve much faster: 3GPPP releases a new standard every 18 months, while, for instance, some of the newest digital communication systems in aviation, such as ADS-B and Controller Pilot Data Link Communications (CPDLC), follow standards that have been frozen for years [62]. To create a sustainable system design for the C3 link, it has to support diverse technologies and identify the key functions needed to guide the software development to bridge between the on-board system and the firmware of the communication modules for each communication technology. For instance, a system built around 5G as the current state of the art in mobile communication should be able to incorporate 6G as it becomes available, while maintaining the architecture and the main functional blocks, as shown in Figure 2.

Among other things, this identification of the functional blocks allows us to put the necessary focus on the control plane of the C3 link, which in turn will allow us to develop system components for network telemetry, the measurement of Quality of Service (QoS), and to use these data to actively select the best available link at any given time of the flight. To distribute the data on the links, an evaluation of their QoS is necessary. Especially in complex network structures such as mobile radio, the QoS can fluctuate significantly and are difficult to predict in contrast to direct connections where functions that calculate the path loss according to the distance to the transmitter can be applied. For example, with cellular connections, latency spikes can occur during the handover between two mobile radio base stations. Moreover, within the context of UAVs connected via mobile radio, there is a degradation of the QoS with rising altitudes [63]. In order to predict these fluctuations before they occur and to be able to initiate countermeasures, if necessary, a Deep Learning (DL)-based QoS prediction model is being developed.

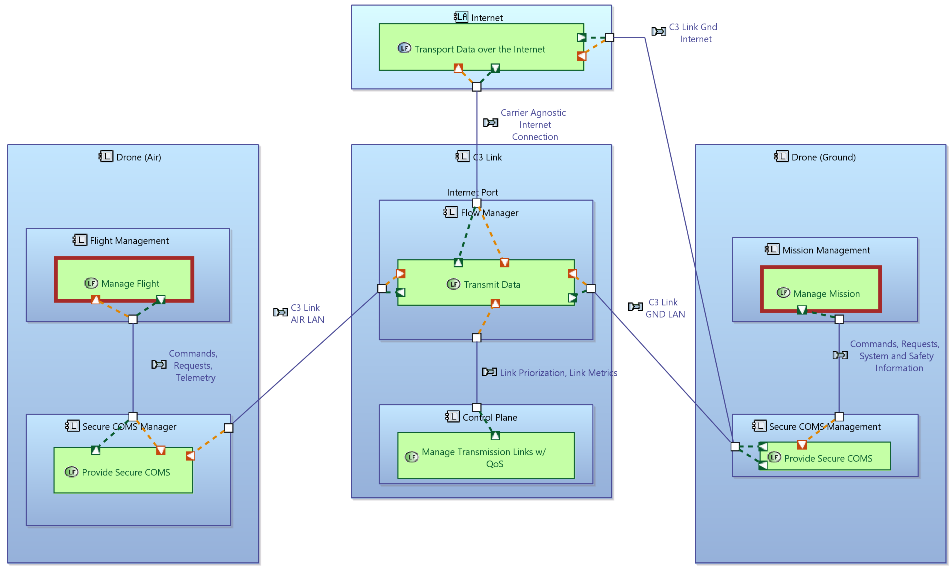

Figure 2. Logical architecture for a C3 Link leveraging a generic, carrier agnostic connection to the internet to enable high availability and QoS.

To support the technology-independent system architecture, three main components are needed for the high-level functioning of the C3 link in this architecture:

- Interface to the data links with an API for the access technologies, allowing us to incorporate new technologies as they become available or as needed to support specific operational scenarios;
- Interface to system component to determine link availability;
- Detecting possible obstacles interface to the QoS estimation and prediction component.

4. Implementation

To enable BVLOS operations in the future, a range of new technologies have been developed and approaches from other industries have been refined to enable a risk-based operation. The following section presents these advancements.

4.1. Functional Modeling

In this work, the Arcadia methodology and the Capella tool were used to improve the robustness of the proposed technologies and architectures. At the operational level, from U-space, the high-level capabilities of “Detect and Avoid”; “Command and Control”; and “Communication, Navigation & Surveillance” are of particular interest. To these, the general capability of “BVLOS Drone Logistic Services” serves as a business motivator and operational driver to frame their deployment.

As an example of this part of the work, Figure 2 shows a Logical Architecture diagram for the C3 link developed by AnyWi. This logical architecture abstracts the C3 Link as a logical entity that transports all messages between the air and the ground. A key concept is leveraging the internet infrastructure, being link agnostic. This allows for the implementation of the architecture for mobile networks, but also of other wireless types such as WiFi or Sat-COM. The architecture thus comprises a QoS function that ensures optimal selection of the best link (or links) to transmit the data. The further development of this logical architecture into the physical level will see the decomposition and allocation of blocks and functions to dedicated physical blocks in the air segment (i.e., drone) and ground segment (i.e., ground station). This logical perspective also makes the re-use of functions between the ground and the air clear.

- Interface to the data links consists of a UDP-based protocol to transmit data in the two directions, from the drone to the ground and the ground to the drone. UDP is chosen here as it allows us to incorporate the highest number of access technologies, from WiFi local links, over mobile networks, to Sat-COM. A specific state machine-based technical architecture is developed, where state machines track the state of each UDP-based connection, as well as the multi-link connection consisting of one or more of the underlying UDP connections.
- Interface to a system component to determine link availability. Links become available, or not available, as the aircraft moves over the flight geography, and the control plane of the C3 link needs to detect this and adjust its algorithms for link selection for each data packet. Current Linux-based systems make this information available via the networking stack and the device drivers, but with a significant delay. For instance, drivers for mobile network modules report the link as available for many seconds after the packet loss has reached 100%. Hence, the control place must detect this situation and react accordingly based on information that it collects itself.
- Interface to the QoS estimation and prediction component. This component is discussed in the section on communication modules.

4.2. Cooperative Detect and Avoid

ICAO defined DAA in ICAO Annex 2 to the Convention on International Civil Aviation [64]: 'Rules of the Air': "The capability to see, sense or detect conflicting traffic or other hazards and take the appropriate action". This definition makes the detection and avoidance functionality even wider and broader than only the detection of other aircraft and having the UAV to avoid them. Looking from this wider perspective, the following functions can be distinguished:

- Detection of other manned and unmanned aircraft;
- Tracking of the detected aircraft;
- Detecting possible obstacles (e.g., buildings, structures, and persons);
- Determining an avoidance maneuver;
    - Avoidance in the sense of 'Remain Well Clear' (RWC)
    - Avoidance in the sense of Collision Avoidance (CA)
- Executing the determined avoidance maneuver.

To perform these functions, the DAA system requires both sensors and computing power, ideally placed on-board of the UA, to perform these functions. Some examples of functionally safe sensors for DAA include Radar, LiDAR, Time of Flight (ToF), or visual sensors, including RGB and infrared cameras, that contribute to navigation via image-based processing. This on-board placement is preferred to ensure a high level of autonomy and reduces reliance on communication systems and possible system failures, especially in the case of highly automated operations. Sensor fusion has been also extensively used to facilitate an accurate navigation output, enabling the aircraft to determine its location and state in a robust way by implementing data from complementary sensors [65]. To handle the inherent limitations of datasets, the Kalman Filtering and Complementary Filtering methods have been proposed. These methods merge data from different sensors, optimizing accuracy by mitigating errors and uncertainties [66].

With respect to the sensor systems, the DAA system is preferably equipped with both cooperative and non-cooperative sensors. A cooperative sensor could make use, for instance, of the already available transponder systems onboard of manned aircraft and new systems onboard of unmanned aircraft, such as Electronic Conspicuity (e-Conspicuity) and ADS-L (Light). A non-cooperative sensor could be a DAA-radar system or other system able to detect and track other aircrafts without any communication. The non-cooperative sensor would also be needed to detect ground obstacles.

Thus, the minimum DAA-system hardware would consist of two sensors and a computer. Taking into account that the system is required on all BVLOS operating UA, this makes Size, Weight, and Power (SWaP) an important aspect of the system, next to the overall safety level, and thus, an airworthiness aspect.

4.3. Communication Modules

The prediction of QoS for mobile radio connections such as LTE, 5G, and, in future, 6G [67], is a current research topic. For example, Machine Learning models have been evaluated by Khatouni et al. [68] to predict the Round-trip Time (RTT) for LTE connections. Especially in the field of automotive for V2X communication, there are several works on predicting the QoS for the mobile network. In this research field, models for V2X communication based on LTE [69,70] as well as 5G [71,72] have been studied. The models applied for the QoS prediction range from Support Vector Machines, Decision Trees, and Random Forest [68–71] to DL models such as Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN)-based architectures [69,73]. The related work presented include model deployment [70] and QoS prediction in the UAV context [73]. There is also work on the interference management of cellular-connected drones. Deep reinforcement learning is applied to optimize path, transmission power, and the cell association vector to reduce interference towards the ground User Equipment (UE) and the UAVs based on simulation [74]. Although this work presents intriguing theoretical findings, our research enables the use of real-world data to train a QoS prediction model in order to enhance the connection between the operator and UAV for the BVLOS use case. In addition, deployment and integration on the UAV poses special demands on the weight and power consumption of the hardware used. In contrast to the previous approaches, the developed system represents a holistic approach that addresses these difficulties, whereby it is integrated into the Multi-Link Communication Gateway.

All software parts are designed to be executable on low weight and power, making them well suited for UAS deployment on an NXP Layerscape FRWY-LS1012A board with an Intel Neural Compute Stick 2 connected via the USB interface. This hardware offers low weight and power consumption but enough processing power for the BVLOS drone use case. An overview of the implemented QoS prediction pipeline is shown in Figure 3. There, the real-time measurement data of the mobile network link is received from the gateway by the Connector. This provides two data streams to the Concatenator: one with Link Parameters which provide the physical parameters of the radio connection, such as signal strength, and a second one feeding the Transfer Parameters containing the properties of the link on the packet level, e.g., RTT. In the Concatenator, the streams are merged with additional UAV data based on the measurement timestamps. The UAV parameter includes, for example, the height above the ground, as the reliability of the mobile radio connection generally decreases with the increasing height [63]. The parameters are then forwarded to the prediction pipeline, whereby the steps marked in green are processed on the CPU and the blue ones are deployed on the AI accelerator. First, a feature reduction is executed based on the variance and the correlation of the features from the training. Subsequently, the value ranges of relevant features are checked and adjusted, if necessary, followed by normalization, which is mainly included to reduce the quantization error induced by the model input. In the next step, the features of multiple measurement points are accumulated as a sequence with fixed length according to the first-in first-out principle. The resulting matrix is fed into the DL model running on the Intel Neural Compute Stick 2. The handling of the data exchange between the CPU and the stick as well as the inference execution is made possible by using the Openvino$^{\mathrm{TM}}$ Inference Runtime.

When designing the model architecture, attention was paid not only to prediction accuracy, but also to model deployment in terms of the usability of individual layers on the Intel stick and model size, and thus also to inference time. For example, unlike the LSTM layers, no gated recurrent units are supported. The model itself consists of an Input and a Batch Norm layer, which is used during model training to reduce overfitting, as well as Hidden Layers, which consists of several connected LSTM, Dropout, and Dense layers. The number of hidden layers, the unit sizes of the LSTMs, and the dropout rate are hyperparameters that were determined using suitable optimization algorithms. Finally, the outputs are generated in a final LSTM and a dropout layer, followed by an output layer consisting of dense nodes. The output includes prediction values for different time horizons for the RTT as well as pseudo-probability values for an occurring edge. An edge is defined as an increase of at least 50% in the RTT between two sample points. The predicted values are forwarded to the Multi-Link Communication Gateway via the connector, where it will be processed to evaluate the usability of the mobile link.

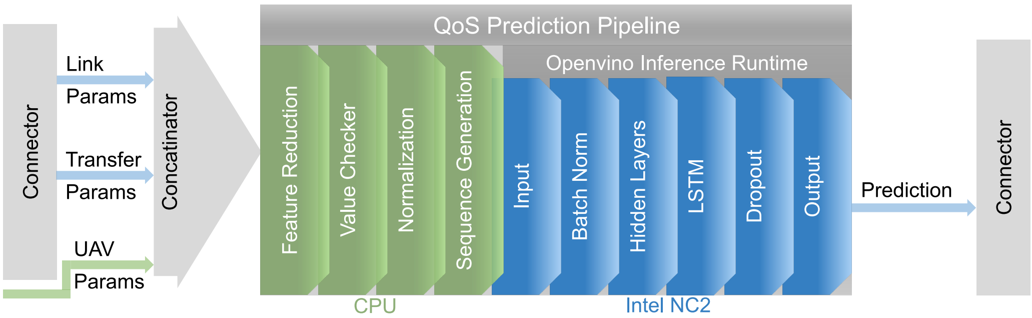

Figure 3. Overview of the QoS prediction pipeline, including the components for interfacing with the Multi-Link Communication Gateway.

4.4. Wireless Safety and Security Layer

The primary function of the WSSL is the detection of communication issues between CPS devices, whether or not they are caused by malicious agents. These issues can be message repetition, packet loss, or inter-message delay. By definition, this is assumed to be the safety layer of WSSL. In addition, WSSL implements a message-signing model, ensuring increased communication security by allowing the receiver to confirm that the received message comes from the correct sender. This signature model guarantees the integrity of the received messages, discarding those with data loss. The Wireless Safety and Security Layer (WSSL) consists of an additional layer to the adopted communication system, implementing a detection process for relevant communication issues, establishing a safe and secure connection between each WSSL endpoint and providing an extra level of confidence to the cyber–physical system (CPS) devices. Its use seeks to increase trust between the sender and receiver since communication failures or malicious interactions can have critical consequences. It can be used in open communication systems where transmissions are unsafe. The implementation is agnostic to the used communication protocols, thus being generically applicable to many use cases, as illustrated in Figure 4.

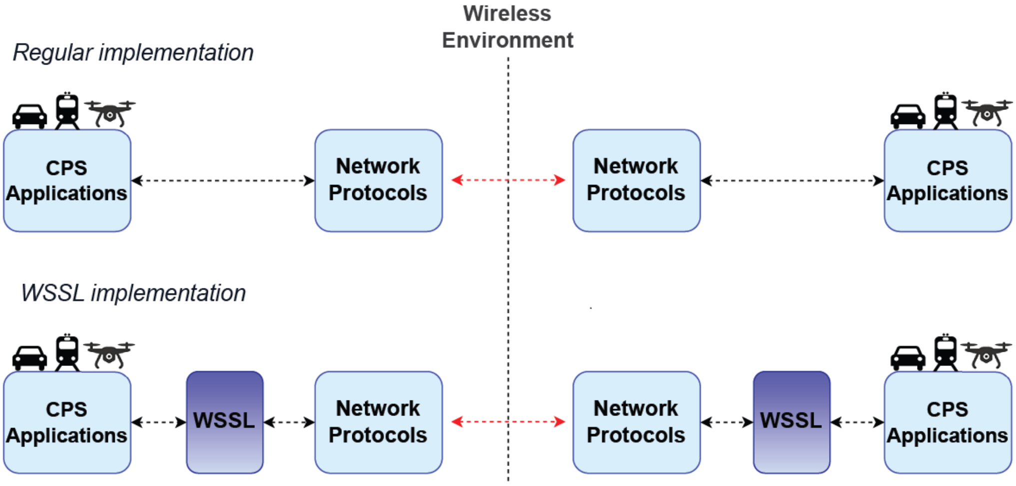

Figure 4. Basic implementation of WSSL.

Considering the diversity of CPS devices, WSSL was developed as a static library compiled in C++. It can be attached to most systems on specific hardware or as part of the original system. Thus, its implementation cost is minimal and its benefits significant, allowing for its application in low-cost or high-performance systems. Although it detects the conditions and problems of the communications network, WSSL does not alter the operation of the device it was implemented in, informing the application about the detection of the event so that the device can handle it.

4.5. Robust Spatio-Temporal Awareness of UAV Swarms

To realize BVLOS operations, accurate spatio-temporal awareness of a UAV is essential. This is typically achieved by exploiting various surveillance methods, e.g., primary surveillance radar (PSR), which measures the distance and bearing of the target. A popular alternative to PSR is the secondary surveillance radar (SSR) system, which considers the aerial vehicle to be equipped with a radar transponder that can respond to an interrogation signal with encoded information about the identity and state of the aerial vehicle, e.g., position and velocity. Modern methods of secondary surveillance include the monopulse secondary surveillance radar (MSSR) and Traffic Collision and Avoidance System (TCAS), or as it is internationally known as, the Airborne Collision Avoidance System (ACAS) [75,76]. The TCAS or ACAS system typically employ SSR in Mode-S operation with an onboard integrator, for cooperative DAA, thus enabling safe integration of UAVs in civilian air spaces [77]. More recently, sensor-fusion-based low-complexity and efficient estimators have been proposed, which offer a more accurate radial velocity estimation as compared to the ACAS [78].

An alternative for SSR methods is the Automatic Dependent Surveillance–Broadcast (ADS-B) system [79], which requires no interrogation signal from the ground. An aerial vehicle equipped with a GPS sensor, an IMU, and an ADS-B transponder can asynchronously broadcast in real time their position, velocity, and identification to aircraft traffic control (ATC) and other aerial vehicles. ADS-B systems are considered to be a key component of the future air transportation system and is mandated by EUROCONTROL in Europe and FAA in the U.S., for all aerial vehicles since 2020 (see [80] and references within).

However, modern ADS-B systems are plagued with noisy data and packet losses, which cause the state of the aerial vehicle to be intermittently unknown. To overcome this limitation, model-based tracking methods for trajectory prediction are typically employed [81,82]. In case of UAVs, advanced neural networks, e.g., Long Short-Term Memory [83,84] have recently shown promising results for accurately tracking the agent trajectory. In the future, for a network of UAVs, distributed state-space models can be employed for reliable tracking of the state variables, e.g., distributed Kalman filtering [85,86] or distributed particle filtering [87,88].

A direct approach to resolve packet losses is to use blind source separation methods; however, these solutions suffer from sign ambiguity and require the number of receive antennas to not be larger than the number of drones/aircraft [89]. More recently, to enable robust UAV navigation, joint range and phase offset estimation algorithms have been developed which enables coherent detection of a single or (collided) multiple ADS-B packets with a significantly lower Packet Error Rate (PER) compared to non-coherent detection methods, as well as it can estimate the range of multiple drones/aircraft using only a single receive antenna [90].

4.6. Autonomous Navigation and Scene Perception

In BVLOS operations, the efficient perception of the UAV surroundings, as well as the safe and fast navigation, are critical for data collection and environmental exploration tasks. This is particularly true in the case of dynamic environments, where the landscape composition is not known in advance and obstacles may appear as the planned trajectory is executed. Therefore, obtaining an appropriate trajectory that safely leads a UAV from its initial position to its final destination is key in autonomous operations.

The recent literature has explored various path-planning techniques for generating optimal trajectories in BVLOS operation in dynamic environments with various obstacles, where the term "optimal" may refer to the path length, time of execution, or energy output. Some examples are graph-based space-search algorithms [91,92], swarm intelligence algorithms [93], artificial potential field (APF) methods [94,95], or reinforcement learning (RL). Particularly, reinforcement learning (RL) algorithms have been extensively used for autonomous navigation as they generate robust and efficient solutions with great performance [43,52].

In this work, we investigated the typical navigation problem for UAVs via unknown environments and dynamic obstacles. The proposed approach is showcased in Figure 5. The performance of two common reinforcement learning algorithms, namely Advanced Actor–Critic (A2C) and Proximal Policy Optimization (PPO), was tested against the traditional graph-based methods A* for obtaining optimal trajectories via dynamic and unknown environments with various obstacles, based on a given map and the actual position of the UAV, the location of its target, and the detected obstacles. Environmental perception was achieved with the deployment of low-cost sensors using the Microsoft AirSim https://microsoft.github.io/AirSim/ (accessed on 15 September 2023) simulator, with four distance sensors attached to a quad copter in the following positions: three sensors, placed in the middle of the drone for detecting the edges of obstacles, and one sensor, placed at the bottom for the distance between the ground and any obstacle below. Through our simulations, we performed a comparative analysis of the proposed algorithms based on the length of the trajectory, flight duration, and safety of flight. In general, the PPO and A2C algorithms demonstrate great performance due to their ability to learn from past experiences and optimize their policy accordingly. Particularly, in our simulations, the PPO algorithm attained an optimal path with a 99% success rate, while it also accomplished trajectories of shorter length in comparison to the other two algorithms. Since RL algorithms are implemented using low-cost sensors, they outperform traditional methods in terms of robustness and efficiency. On the contrary, the A* algorithm is a solid and reliable solution for path-planning problems, although they rely more on expensive LiDAR sensors, and therefore, are computationally more complex. After several training epochs for the Reinforcement Learning algorithms that we trained (A2C and PPO), we resulted in a significantly better performance for PPO compared to the performance of an implementation of A* that gradually finds a path to the target (end-point) while learning the obstacles ahead.

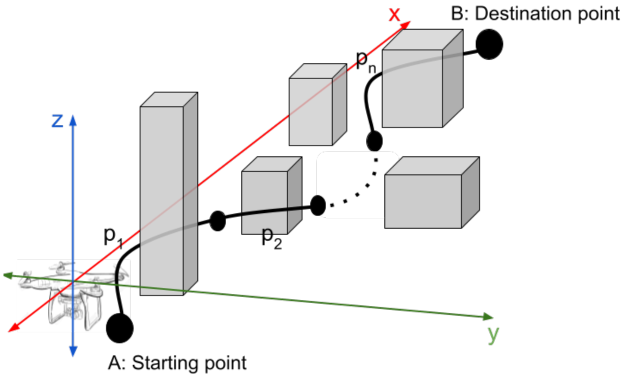

Figure 5. An abstract view of the obstacle avoidance approach.

4.7. Seamless Integration of Proposed Technologies

In order to integrate the proposed QoS prediction model into a multi-link communication gateway, the software interface have been implemented. Moreover, the modules are optimized to be deployed on low-weight and low-power devices. The WSSL can be added on top of the gateway and on the ground control site to facilitate the interface between the flight controller/ground control and the communication stack. A further description of the gateway architecture, including QoS prediction and WSSL, is presented in the publication by

Purucker et al. [96]. In theory, the proposed navigation and communication technologies can be integrated onto a single platform, while real-time data processing and onboard computing capabilities further enhance the autonomous navigation of UAS, allowing for dynamic decision making in complex environments. However, significant integration work is required to deploy everything onto one computing platform, ensuring the integration of navigation and communication software into one cohesive system. Seamless integration of navigation and communication systems requires careful consideration and innovative solutions to ensure safe, efficient, and reliable operations. By combining multiple navigation technologies, the performance and reliability of UAV navigation systems can be enhanced. Standardized communication protocols can be implemented to ensure high-speed and low-latency data interaction between UAVs and other heterogeneous networks, while the utilization of smaller, lower-power consumption inertial guidance systems that are well suited for UAV payloads can leverage navigation accuracy and reliability. Finally, ensuring the security and privacy of communication transmissions via the encryption of communication channels and secure data storage is another critical issue that requires significant attention.

5. Discussion

5.1. Societal Acceptance of BVLOS Operations

As drone technologies continue to emerge with obvious benefits along the way, it remains uncertain whether the public opinion and perception is for or against adopting UAS. Technological and scientific improvements as well as the development of more reliable frameworks aim to further boost their adoption in the future. Although the UAV market already has a great variety of hardware, software, and operational products to offer, the key element for their successful implementation is hardly defined by those aspects but largely depends on the adoption of its users and, more importantly, on the acceptance of the wider public. However, it also largely depends on their integration and the conformance of the final results to local regulation [3]. Without the wide acceptance of society, drones will be unable to exploit their considerable potential as tools for smarter cities. The key to unlock the potential of drones, and allow for their applications to bloom, is to integrate them within the daily routine and activities of society. Since UAVs are still at a low level of implementation, collecting actual experiences by users remains a challenging task [97]. Another critical aspect for the wider adoption of UAS technologies are the cost implications. As industries increasingly explore the potential benefits of UAVs, understanding the financial considerations becomes paramount. The initial investment required for the acquisition and implementation of UAV technologies, coupled with ongoing operational expenses, training, and maintenance costs, directly influences market adoption against the evident benefits of UAV usage. In recent years, manufacturers have been focusing on the development of UAVs that are cost effective. This is driven by the reduction in the price of UAS components such as sensors, controllers, and batteries due to technological advancements and investments in drone hardware worldwide, as reported in [98].

5.2. Regulatory Considerations

BVLOS demands levels of autonomy and collaboration that have hitherto only been seen in the autonomous vehicle market. It is expected that technologies developed for those markets can be exploited for drone application. Technology can, however, only enable the compliance of operations with the regulatory framework which must also be defined. Fortunately, that process is already in flow with U-Space, building and testing the operational and regulatory framework that enables this new dawn from a regulatory and compliance perspective. SESAR (Single European Sky Air Traffic Management Research) has already started work on regulatory and procedural structures for drone co-existence with crewed traffic with the U-Space architecture and has defined levels of implementation of that architecture U1–U4, covering the period from 2019 to 2035. This will demand new technical capabilities that are not available at realistic price points today. That is not to say that these technologies will be created in a vacuum—many of them already have analogues in the 'traditional' aerospace arena. Alongside that, the drive for connected and autonomous automobiles has also created impetus for some of these pieceparts at price points and multiplicities that the traditional aerospace industry can only dream of. Industrial innovation in the aviation domain, and in the domain of unmanned flight in particular, can only be successful if carried out in concert with other roadmaps for regulatory development and operating standards and procedures [99].

5.3. Open Issues and Challenges

Extended autonomy of UAS enables us to cover far greater distances, with a lower cost and a reduced risk to human life; however, it also raises new challenges, as it creates a new landscape for communication, navigation, and flight under varying conditions. Regarding UAs' communication reliability, there is no established standard for the communication link in drone communication. While potential communication technologies, such as the fourth and fifth generations of cellular network technology (4G/5G), exist, they face significant drawbacks, with 5G still in the process of full deployment and a reliance on ground-based infrastructure. Therefore, developing robust communication protocols, exploring new frequency bands, and implementing advanced signal processing techniques to enhance reliability are critical areas for further research. Accomplishing safe and efficient UAS operations may be dependent on the transmission and reception of data, the execution of software functions, and environmental conditions such as higher wind speed [3]. Advanced aerial autonomous, intelligent, and safe navigation in complex scenarios requires specific algorithms with multimodal path-planning optimization, as taking into account only simple optimization criteria (energy consumption, path length, and object avoidance) may be insufficient. Despite the recent advances in developing ML-powered networking protocols for UAV networks, there are still challenges and issues that would be the center of attention for the coming years. From the communication perspective, most technical challenges arise from the limited payload, processing power, and the structure-free and highly dynamic nature of unmanned aerial platforms [100]. Moreover, UAS navigation needs to take place in a more dynamic execution environment that will provide the flexibility to allocate and deallocate resources at runtime depending on the task objectives, maintaining the necessary tradeoff between the conflicting requirements. These challenges highlight the need for ongoing research and development in the field of UAS technologies to ensure safe, reliable, and efficient integration into the airspace.

6. Conclusions

This paper presents the challenges that state-of-the-art technologies face for supporting BVLOS drone flights. It is pointed out that, in order to facilitate risk-based flight missions for BLVOS operations, further enhancements of the technologies are essential to ensure their maximum reliability and minimal risk of failure. Therefore, in this paper, the concept of a risk-based approach to BVLOS operations is investigated, aiming to address the challenges and uncertainties associated with these operations while promoting their safe and efficient integration into the airspace. Specifically, the combination of technological components, architectures, and protocols that drive future UAS growth was presented, while related opportunities and challenges were discussed. In order to future-proof the systems and facilitate their development, a drone reference logical architecture was developed using the Arcadia and Capella tools as exemplified in Section 3, with reliable communications. In the process, we prioritized understanding the intersection between the market and operational demands while identifying integration necessities among the various capabilities. The enhanced technologies treated in this paper encompass collision avoidance methods, namely Cooperative DAA and ADS-B, communication systems incorporating redundant connections, QoS prediction algorithms, and a safety and security framework, in addition to reinforcement-learning-fueled autonomous navigation and scene perception capabilities. To conclude, with this paper, several key pillars towards autonomous BVLOS operation according to the U-space are addressed. Finally, we set the scene for future research towards realizing the full potential of BVLOS into the rapidly evolving airspace.

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