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Edge Computational Offloading for Corrosion Inspection in Industry 4.0

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Abstract—The fifth generation (5G) mobile networks are a game changer for the 4th industrial revolution (Industry 4.0). The difficulty of developing vertical applications for mobile networks is however still challenging. This paper proposes a new paradigm solution to significantly facilitate deploying network applications (NetApp) closer to the end user and improving the user experience, facilitated by 5G. This new paradigm leverages flexible service onboarding and composition end to end, and computation offloading to a Multi-access Edge Computing (MEC) platform to meet the demanding requirements of the NetApps. A functional prototype is developed and empirical comparison is conducted to validate and evaluate the performance of a corrosion detection NetApp using artificial intelligence (AI) in three different scenarios where the application is hosted. The prototype runs this NetApp over an Unmanned Aerial Vehicle (UAV) connected to a 5G network testbed, and the results offer insights into this performance improvement and elaborates how opting for this NetApp solution can help the industry. In this case, the use of this NetApp can achieve a 55.47% reduction in computation time and improve corrosion identification processing time by 25.5%.

Index Terms—Edge Computational Offloading, NetApp, 5G Network, UAV, Corrosion Detection

I. INTRODUCTION

Industry 4.0 offers a comprehensive, intertwined and resilient approach to manufacturing by relying on the interconnectivity of the Internet of Things (IoT), access to real-time data, and cyber-physical systems. The industry 4.0 increases quick and low-cost productivity. In Industry 4.0, the manufacturing systems communicate, analyse and utilise gathered information to guide intelligent actions. It also includes avant-garde technologies such as additive manufacturing, robotics, artificial intelligence and augmented reality among others [1].

The Fifth Generation (5G) mobile networking is a key enabler to meet the networking requirements in Industry 4.0. 5G technologies will trigger great opportunities for many vertical industries including manufacturing, public safety and many more by offering novel business and innovation models. However, the knowledge gap between the vertical industries, the telecommunication experts and the developers may be a hindrance to the adoption of 5G solutions. The Network Application (NetApp) is a main enabler for the adoption of 5G solutions as it hides the complexity of the 5G infrastructure for the developers and reduces the development time of the services and thus, optimise the usage of 5G resources [2].

NetApp is a group of networked Virtual Network Functions (VNFs) developed by vertical developers for a specific use

case which is deployable over 5G and beyond networks infrastructure including edge located within a Radio Access Network (RAN), core network and so on. Low end-to-end latency and real-time reaction are vital for NetApps, especially in AI-based critical missions. These VNFs are usually deployed by vertical business services which try to leverage computationally expensive resources to the edge or the core of the network. Besides, NetApps, as cloud-based applications, can be deployed on demand and include User Plan Functions (UPF), AMF (Access and Mobility Functions), SFM (Session Management Functions), etc.

AI-IoT applications such as object detection generate large amounts of data and consumes a lot of energy, memory and computational resources. Many of these applications require intensive computation and low latency. Although IoT devices are becoming more powerful, the battery, CPU and memory are still inadequate for large applications. Edge Computation Offloading is one of the solutions in which the computation is performed at the edge of network. It reduces latency and energy consumption and improves the performance of IoT applications [3]. Edge computing is beneficial when compared to local and cloud computing. When compared to local computing, edge computing can overcome the restrictions of computation capacity on end devices. It can also reduce latency caused by computational offloading to the remote cloud [3].

Many European projects has been conducted by European Commission to show the benefits of edge computational offloading. As a case in point, loud aimed at Proactive management of Cloud Resources Management at the edge for efficient real-time processing of Big Data [4]. In another European project [5], a scientifically sound and industrially validated model was developed for doing general-purpose computation on edge networks to reduce latency. In addition, in [6] a novel data offloading decision-making framework is proposed, where users have the option to partially offload their data to a complex Multi-access Edge Computing (MEC) environment, consisting of both ground and UAV-mounted MEC servers. The problem is treated under the perspective of risk-aware user behaviour. In our study, the result of a NetApp (corrosion detection) has been analysed to show the effectiveness of offloading solution. In another study [7], a frame work for multi-UAV-assisted two-stage MEC system is proposed and evaluated in which UAVs provide the computing and relaying services to the mobile devices. Due to the limited computing

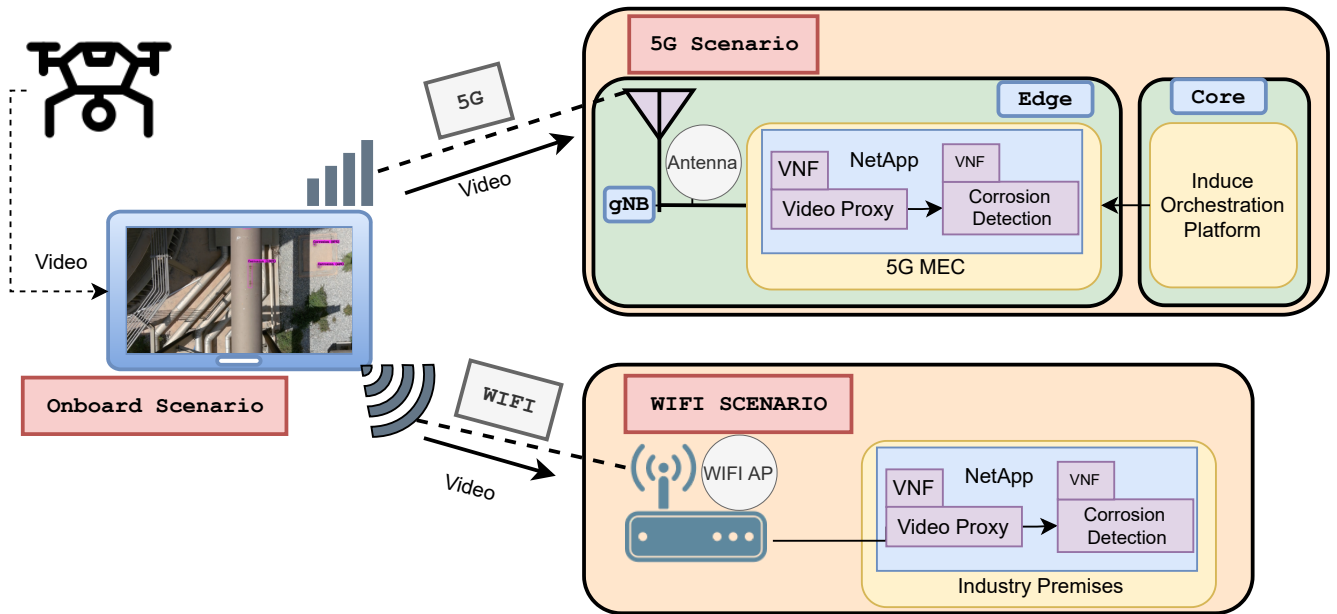


Fig. 1. Schematic diagram of three experimental scenarios: Onboard execution of AI, WIFI-based and 5G-based NetAPP deployment.

resources, each UAV executes a part of the offloaded tasks and in the second stage, each UAV relays the portions of the tasks to the terrestrial base station which has enough computing resources enough to handle all the tasks. In our study, the UAV is just transmitting the video and all the computation of the corrosion detection application are offloaded on the edge. In [8], an overview of RIS-assisted MEC systems was provided and four use cases were evaluated for reducing processing latency and improving energy efficiency. This technique can be adopted to further reduce latency in our study as future work. In another study [9], the authors showed how UAVs can be used for crowd surveillance based on face recognition using the Local Binary Pattern Histogram (LBPH) method in OpenCV library. To evaluate the offloading of video data processing to a MEC node was compared to the local processing of video data onboard UAVs. The reported processing time is slow for our use case.

All these projects shed light on the importance of edge computational off-loading.

In this article, a novel NetApp architecture is designed and developed in the context of 5G-INDUCE project [10], which detects corroded areas on critical infrastructures at the edge of the network using Unmanned Aerial Vehicles (UAVs) and meeting the strict networking requirements in order to improve work safety, environmental protection at low cost. In other words, the aim of this article is to demonstrate the fact that by deploying the NetApp outside the local device, the performance of the application will be considerably improved, achieving a faster processing time than performing the processing on the device itself due to making better use of resources by using corrosion detection as a use case to evaluate the prototype.

The remainder of the paper is organised as follows. Sec-

tion II introduces the NetApps and its architecture based on UAVs. The corresponding experimental results are presented in Section III. Section IV concludes the paper.

II. UAV-BASED NETAPP DESIGN

In order to demonstrate the concept, an automatic UAV-based NetApp is designed and prototyped for monitoring early corrosion detection on critical infrastructures such as pipes and tanks to warn the experts to take immediate action.

Corrosion is a gradual destruction of structural material properties due to interactions with the environment that results in damage and failure of global infrastructures in the long run. According to World Corrosion Organization, the financial loss associated with damages to global infrastructure is 2.5 trillion USD. It is delineated as one of the key defects and a hazardous phenomenon which has a significant impact on the economy and safety. Hence, monitoring and early corrosion detection on critical infrastructures are of myriad importance to reduce the cost and maintain the safety of human lives [11].

This Unmanned Aerial System (UAS) for corrosion detection is composed of three main entities: a drone, a controller and a tablet. This study which is presented in fig 1, compares three different scenarios to accomplish the task of corrosion detection from a UAV. The first scenario only considers the execution of the AI embedded on the tablet, therefore there is no wireless connection to rely on at this point. In the second and third scenarios, the tablet is connected to a WIFI network and a 5G network respectively. In both scenarios, the same NetApp is used for the corrosion detection.

In the first scenario, the tablet executes the pipelines involved in corrosion detection. Once the video is received from the drone, each frame is decoded and pre-processed to be converted into a suitable format for the AI algorithm. The

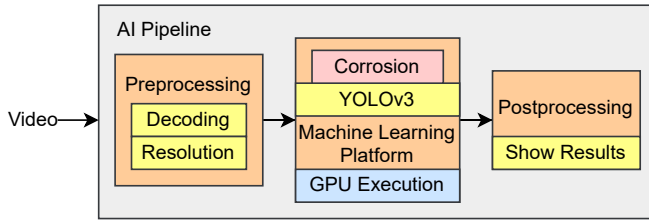


Fig. 2. AI process of a single frame since it is decoded until the results are shown on the screen.

video is transmitted from the UAV to the controller through wireless connection named “OcuSync”. Although the camera records at 4k resolution, the streamed video has the resolution of 1280x720. OcuSync protocol has a communication latency of 28ms. However, this manuscript only considers the communication latency from the tablet to the edge of the network and the evaluation compares the execution on the tablet versus the execution on the edge. Afterwards, the algorithm is executed on a GPU [12] in order to provide the detection results (bounding box of the corrosion presented in the image). Finally, the bounding boxes are overlaid on the streaming video being monitored by the pilot.

In the WIFI-based and 5G-based NetApp solutions, the proposed UAV-based corrosion monitoring system comprises two VNFs: a video proxy and a corrosion detection system. The video proxy VNF receives the video sent by the tablet and forwards it to the corrosion detection VNF. The corrosion detection VNF executes the same AI algorithm in the onboard solution although it is deployed on the edge over high-spec hardware.

The algorithm chosen to detect the corroded areas is YOLOv3 [13]. YOLOv3 is a very good choice when real-time detection is needed without losing too much accuracy which is the requirement of this study. YOLOv3 has achieved 55.3% of accuracy using COCO dataset [14]. Nevertheless, YOLOv3 is retrained and evaluated with a corrosion dataset defined in subsection III-A.

Figure 2 illustrates the pipeline needed to provide the detection results. This AI pipeline is executed in all three experimental scenarios in this study. In the pre-processing stage, each frame is decoded and prepared as an input for the algorithm execution. This preparation includes resizing of frames from 1280×720 to 416×416 pixels. The second stage is the execution of the YOLOv3 algorithm. YOLOv3 receives the frame and it is executed over the Machine Learning Platform (TensorFlow in this use case) with GPU compatibility (NVIDIA in NetApp scenario and Snapdragon in the onboard scenario). Finally, the output of the CNN is post-processed to produce the results containing three values: produces the output in three components: the bounding boxes which shows the location of corrode areas, the class of the bounding box and the probability score for that prediction.

In the WIFI scenario, once the video is received from the drone, the tablet is merely in charge of transmitting each frame to the NetApp where the AI is deployed without processing

any information using WIFI technology. This scenario is suitable for use cases where WIFI connection is accessible. The main advantage over the onboard scenario, is that the NetApp runs on a device external from the local device where the video is collected. This makes the execution time faster than when the whole process is performed on the same device. The WIFI technology used is “WIFI 6” at 5 GHz.

The third alternative considered is the use of a 5G network to study how it improves the NetApp usage at the edge of the network with respect to the onboard scenario. This is the third scenario studied where the NetApp, as mentioned previously, has been installed in the network edge specifically in the 5G MEC (Multi-access Edge Computing). This 5G capability allows the services to be executed close to the users to have a quick response and interaction without affecting the operation of the NetApp. Having an acceptable delay in the transmission of the video from the tablet to where the NetApp is deployed would provide real-time results for corrosion detection. In figure 1, the every deployment of the NetApp is illustrated.

To deploy 5G network for this use case the OpenAirInterface software [15] was used to generate both the core and the RAN of a mobile network and to which the tablet has been connected for video transmission through a programmable SIM card.

III. RESULTS

This section shows the results obtained by comparing the three experimental scenarios for corrosion detection. It demonstrates the advantages and disadvantages of porting the computation from the user equipment (UE) to the edge of the network. It also presents the possible bottlenecks to tackle in future work in order to improve the system.

A. Experimental environment

Figure 1 shows the different scenarios studied for performance comparison. For the first scenario (Onboard), the video received from the drone is processed and the AI detects the corrosion on the device itself. In the second scenario (WIFI-based), the video is first transmitted to a computer where two docker containers are deployed before being processed. The video is transmitted from the UAV to the controller through wireless connection named OcuSync. Although the camera records at 4k resolution, the streamed video has the resolution of 1280x720. The UDP protocol has been chosen for video transmission in order to have a faster transmission. The first container is an Nginx server which converts the video received using the UDP protocol and forwards it to the second container using the RTMP protocol. This conversion is needed in order to allow multiple clients to connect and receive the video in a one-to-many communication style. The second container hosts the AI and responsible for detecting the corroded area in the video. The third scenario (5G-based) behaves in a similar manner as the WIFI-based scenario.

For the experiments, a Samsung Galaxy Tab S7+ 5G Android tablet with a Qualcomm Snapdragon 865 processor and 8GB RAM was used. In the WIFI-based scenario, the

GPU was a GeForce GTX TITAN X 12GB. For the 5G-based scenario, all the experiments were executed on a computer with an Intel Xeon(R) CPU E5-2630 v4 @2.20 GHz x 10 with 32 GB RAM running UBUNTU 18.04. A GTX TITAN X GPU with 12GB RAM was used to run the AI-based model. The Core used for the 5G network is the OAI-5GCN developed by OpenAirInterface. The version used is 1.4.0. Regarding the RAN, it is deployed on the same computer as the Core, Nginx and AI containers. For this study, a Universal Software Radio Peripheral (USRP) X310 was chosen. For the antenna, one of the Bluespot brand covering 5G n78-band was chosen. The drone used for the video transmission was a DJI Mini 2 which streams the video at 1280×720 . In addition, to make a fair comparison, the bandwidth and bitrate were considered the same (7.5-8.1 Mbps) for both the 5G and WIFI networks. The video streamed from the tablet has a resolution of 1280×720 pixels and 24 fps. Moreover, in both scenarios, the access point used by the tablet to transmit the video was at the distance of one meter. The two scenarios were similarly deployed to be comparable.

Dataset: In order to train the convolutional neural network (YOLOv3 in this use case), a UAV-based data collection were performed by PPC (<https://www.dei.gr/>) from 5 to 10 meters of altitude. The data were collected at PPC critical infrastructure considering complex background, different scales, angles, orientations, sizes and altitudes. 2K live videos of pipes and tanks with corroded areas were collected and still images were extracted from the collected videos for further processing. Totally, 2000 images were extracted and manually annotated to create the training dataset.

B. Quantitative Results

As in the WIFI-based and 5G-based scenarios, a wireless connection is involved from the Android tablet to the AI VNF. Several metrics were measured such as lost packets, delay and jitter during transmission as these may affect the detection performance. The existing delay in the video transmission has to be taken into account in these scenarios as it can affect the speed of obtaining the results of the AI-based corrosion detector in this case study.

During the experiments, three key points in the infrastructure are used to collect the Packets Capture (PCAP). These are the tablet and both containers that hosted the Nginx and AI. Then, the packets' timestamps at the source (round trip) were obtained in order to calculate the delay during transmission. Also, packet loss and the jitter values are obtained from those files.

In the case of the onboard-based scenario, the only time taken in the experiments it is the time for the AI model to provide the detection results once the video is received from the drone. For the WIFI-based and 5G-based scenarios, we had to calculate the time it takes for the transmitted video to reach the Nginx, then the time it takes for the Nginx to convert the video from UDP to RTMP and then, the time it takes for the AI to detect the corroded areas.

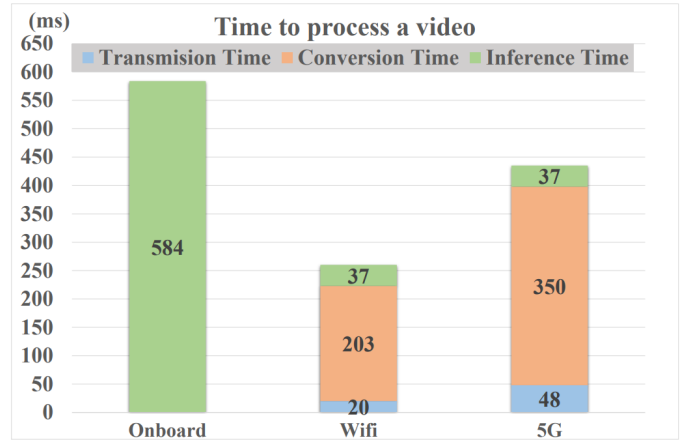


Fig. 3. Video processing time in 3 scenarios

Figure 3 displays the different times taken to detect the corroded areas on the video. For WIFI-based and 5G-based scenarios, the total processing time comprises the transmission time, the video conversion time and the inference time. For the onboard solution, where the AI is executed locally, the corrosion detection time is only measured.

As can be seen in the Figure 3, the time it takes for Nginx to convert the video varies in 5G-based and WIFI-based scenarios. This is because during the conversion, Nginx waits for a minimum number of packets to be able to transmit the video again. This is due to the fact that there is more delay in the 5G network than in the WIFI network, and Nginx has to wait longer to be able to transmit the video.

Therefore, a decrease in the delay between the transmitter and the receiver will make the conversion time smaller and consequently, the corrosion can be detected in a shorter time. This fact can be seen in the scenario where WIFI technology is being used, as we have a shorter delay and thereby the total time is shorter. Based on this experiment, the Nginx VNF is identified as the bottleneck of the NetApp solutions. By contrast, the onboard scenario bottleneck relies on the execution of the AI model. As assumed in the previous section, this process is computationally expensive and thus, the tablet cannot operate an inference time of more than 2 fps. In contrast, due to the abundant computational resources available, the NetApps solution achieves an inference time of 37 ms.

The packet lost during transmission in both scenarios were almost 0%. The percentage of packets lost in the WIFI-based scenario is 0.012%, while the 5G-based scenario is around 0.01%. With these values, packet loss is not an issue to affect the AI-based detection process.

The last metric measured to study video transmission quality is jitter. This parameter is defined as the variation in delay of the different packets arriving at the destination. A high jitter value may cause problems when processing the video in the AI model. Hence, it is necessary to study it in communications involving video or audio, especially if they are in real-time.

TABLE I
RESULTS OF THE WIRELESS TRANSMISSION FOR BOTH 5G AND WIFI.

	WIFI	5G
Jitter	15.4 ms	16.3 ms
Packet loss	0.012%	0.01%
Delay	20 ms	48 ms

In both scenarios (WIFI and 5G) the jitter values are 15.4 and 16.3 milliseconds respectively. These small values are an indication of good quality transmission. Table I shows a summary of the metrics obtained for the wireless (WIFI and 5G) transmission. The obtained results clearly emphasize of the fact that by embedding the AI-based model on edge, we get faster execution time.

Although the CNN-based corrosion detection model performance is not the main focus of this research work, it achieved a total accuracy of 66.13% with the collected dataset. Due to the training dataset being collected from critical infrastructures at PPC premises and being very challenging, the accuracy obtained is a good starting point. This will be further modified and enhanced to achieve better accuracy planned as our future work. For the onboard scenario, the model size is a total of 224 MB. In contrast, the same model deployed in the NetApp scenario is less optimised and has a size of 248 MB. This is due to the fact that Android requires an special

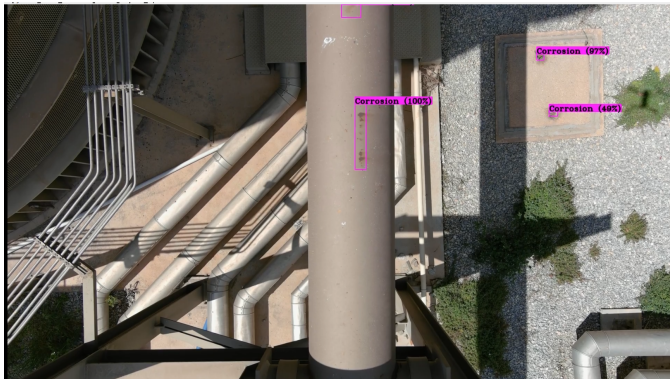


Fig. 4. Corrosion detection on pipes.



Fig. 5. Corroded areas on critical infrastructure.

conversion of the model to Snapdragon GPU which optimises the weight of the model. In terms of inference time, the onboard solution takes 594 ms (1.68 fps) per frame when executing the algorithm. However, the NetApp solution only takes 37ms (27 fps).

According to the results, both NetApp scenarios provide faster results than the onboard solution by 25.51% (5G) and 55.47% (WIFI) respectively. Furthermore, the probabilities of detected areas has also been improved. While the onboard solution misses 22 frames per second, the NetApp solution is able to perform detection on every frame received and thereby enhancing the chance of corroded area to be detected in the NetApp scenarios. T

C. Qualitative Results

In this section, the detection results of corroded areas have been shown visually. To achieve these results, separate unseen testing videos were taken in real scenarios at PPC industrial sites. Fig. 4 shows detections of corroded areas on pipe. Fig. 5 presents a scenario with a more complex, and cluttered environment.

IV. CONCLUSION

This research work provides an empirical demonstration of an edge computational offloading system for corrosion inspection by using distributed Virtual Network Functions. The presented NetApp will benefit vertical businesses to inspect their critical infrastructures for corrosion with high performance by leveraging edge computing capabilities. The implemented prototype and experiments have demonstrated the benefits of computational offloading from the UE (User Equipment) to MEC by taking advantage of the computational resources available whilst improving the performance of the application. Significant performance improvement has been achieved in the empirical study. When executing the NetApp on edge, the proposed solution can achieve a 55.47% reduction in computation time and improve corrosion identification processing time by 25.5%. The proposed prototype can also be widely used in plethora of applications such as military, surveillance, search and rescue (SAR) operations, precision agriculture, and infrastructure inspection. In future work, the accuracy of AI-based corrosion detection model will be enhanced. In addition, in order to make a much more complete study, the energy consumed in the 3 scenarios will be studied. Reducing the bottleneck in the streaming of the video will also be further explored in two ways. First, by increasing the bitrate performance when converting the video from UDP to RTMP. Finally, OpenAirInterface is currently still under development, therefore, delay-related results with this technology are not optimal. As time goes on, the delay will be reduced.

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BIOGRAPHIES

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Gelayol Golcarenenji is a Postdoctoral research fellow in artificial intelligence at University of the West of Scotland (UWS), UK, where she is working on the 5G-INDUCE, NG-RPAS and Arcadian-IoT European projects. Her current research interests include, artificial intelligence, machine learning, deep learning methods and applications. Previously, she was involved in 'Smart crane Real-Time Object Detection' and 'a Smart Remotely Piloted Aircraft Systems (S-RPAS) for Real-Time detection of missing people and she and her

team won the CEED-SCOTLAND innovation award, and UK Times Higher Education (THE) Awards 2021 knowledge exchange award for the project. She received her Ph.D. degree from Deakin University, Australia, where she was involved in the automation of carbon fiber production line using image processing and industrial machine learning techniques. Her research to date has resulted in more than 20 peer reviewed journal papers, conference papers, and book chapters.

Ignacio Martinez-Alpiste is a Postdoctoral Researcher in Artificial Intelligence at the University of the West of Scotland, UK. He is a winner of the UK Times Higher Education (THE) Awards 2020 — Knowledge Exchange and the 2020 Scotland CeeD Industry Awards — Innovation Award. He is Co-Investigator for the CENSIS S-RPAS, SmartCranes, NG-RPAS and for EU Horizon 2020 funded projects (SELFNET, 5G-INDUCE and ARCADIAN-IoT). His main research interests include AI with applications in Unmanned Aerial Systems, 5G networks and video networking, among others. He is also a reviewer of international scientific journals and conferences. He received his Ph.D. at the UWS.

Jose M. Alcaraz Calero [SM] is a Professor in Networks at School of Engineering and Computing at the UWS. He is an IEEE Senior Member with experience in 5G networks, network slicing, monitoring, automation and management. In the academic side, he has more than 150 publications in SCI-indexed international journals, conferences and books. He has been involved in 20 editorial activities in the most prestigious journal in the field and served as chair in 20 international flagship conferences and contributes as Technical Programme Committee member in more than 100 international conferences. In the industrial side, he has more than 50 patents and intellectual property rights. From the leadership perspective, he has significant experience as Principal Investigator or as Co-Investigator in more than 20 research projects at local, national and especially at European and international level. He is the Co-Technical Manager for EU Horizon 2020 projects SELFNET and SliceNet.