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Facilitating mmWave Mesh Reliability in PPDR Scenarios Utilizing Artificial Intelligence

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ABSTRACT The use of advanced AR/VR applications may benefit the efficiency of collaborative public protection and disaster relief (PPDR) missions by providing better situational awareness and deeper real-time immersion. The resultant bandwidth-hungry traffic calls for the use of capable millimeter-wave (mmWave) radio technologies, which are however susceptible to link blockage phenomena. The latter may significantly reduce the network reliability and thus degrade the performance of PPDR applications. Efficient mmWave-based mesh topologies need to, therefore, be constructed, which employ advanced multi-connectivity mechanisms to improve the levels of connectivity. This work conceptualizes predictive blockage avoidance by leveraging emerging artificial intelligence (AI) capabilities. In particular, AI-aided blockage prediction permits the mesh network to reconfigure itself by establishing alternative connections proactively, thus reducing the chances of a harmful link interruption. An illustrative scenario related to a fire suppression mission is then addressed by demonstrating that the proposed approach dramatically improves the connection reliability in dynamic mmWave-based deployments.

INDEX TERMS Mesh networks, millimeter wave communication, artificial intelligence (AI), wireless communication, public protection and disaster relief (PPDR).

I. INTRODUCTION

Wireless communication technologies are an essential enabler in Public Protection and Disaster Relief (PPDR) situations [1], [2]. They were historically utilized to provide sustainable voice communication services for public safety agencies [3]. Today, the cutting-edge PPDR applications include a variety of multimedia services [4] complemented with artificial intelligence (AI) capabilities [5]. This decisive transformation promises advanced situational and contextual awareness as well as enables event prediction and prevention in critical missions. The use of AI in PPDR contexts may lead to an upgrade of mission-critical communication to mission-critical assistance.

For its efficient operation, AI-based technology requires real-time information about both the problem and the context [6]. Computer vision systems and related video analytics can be efficiently employed to collect it. For instance, video information about a specific PPDR event may be obtained with on-body cameras of the rescue crew members (police officers, firefighters, ambulance doctors, etc.) [7], video surveillance cameras deployed across the area of the PPDR mission [8], or with the aid of robots (e.g., unmanned aerial and ground vehicles) [9], [10]. Since data mining from the video stream requires relatively powerful computation capabilities, it can be performed in a remote processing center or in a distributed fashion via edge/fog computing. Both approaches require high-throughput radio access networks.

The emerging millimeter-wave (mmWave) technologies, such as IEEE 802.11ad/ay [11] and 3GPP New Radio (NR) [12], [13], offer the throughputs on the level demanded by traffic-hungry PPDR applications [14]. However, their utilization in PPDR scenarios is hampered by a

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number of challenges. First, there is uncertainty about the existing communication infrastructure, which can be partially or completely unavailable. Second, mmWave propagation is sensitive to atmospheric, weather, and other conditions, which may eventually cause severe link quality degradation. These adverse effects may drastically reduce the reliability of mmWave connectivity.

The PPDR applications are expected to operate in dangerous conditions, such as fire, smoke, gas, or water vapor [9], which may affect the propagation of the mmWave signal [15]. Furthermore, certain PPDR situations may inherently deteriorate the propagation conditions; for example, substances applied by firefighters may occlude the direct path between the communicating nodes. The use of mmWave *mesh* topologies can provide diverse paths between a source and a destination, and thus partially address these challenges by enabling proximate communication when the network infrastructure is unavailable.

The problem of link blockage has been identified as one of the most challenging for mmWave communications. Particularly, it affects connection reliability in both single-hop and multi-hop topologies. In recent literature, this issue is primarily tackled by employing reactive techniques along with standardized capabilities, such as multi-connectivity operation [16], when the association point is only changed when the current links experience outage conditions as the result of a blockage situation [17]–[20].

Hence, contemporary mmWave solutions rely on inherently reactive techniques to mitigate dynamic link blockage events [16], [20]. This approach may introduce harmful delays in data transmission, thus hampering the use of real-time PPDR applications, since it permits radio connections to become interrupted and then recover later. Alternatively, one may use *proactive* mechanisms by predicting blockage situations and taking action in advance [21]–[23]. Possible measures may include altering the trajectory of movement to avoid blockage or utilizing alternative data routes, e.g., via peers that establish backup links. To efficiently enable this functionality, one has to employ advanced prediction techniques.

In this work, we analyze the use of AI methods to enable uninterrupted mmWave mesh connectivity in PPDR scenarios. Consequently, we contribute a novel approach to mitigate dynamic link blockage in mmWave mesh systems. It utilizes AI-aided prediction of blockage situations and helps establish alternative connections via peer relays before the blockage has actually occurred. Numerical results reported in what follows demonstrate the feasibility of our proposal. Particularly, the outlined approach considerably reduces the fraction of time when at least one node of the mmWave mesh in question is disconnected from the rest.

The remainder of this paper is organized as follows. In Section II, we discuss the use of mmWave technologies in PPDR situations. In Section III, we review the use of AI in the context of mmWave mesh technologies for PPDR. Our illustrative scenario is then studied in Section IV. The conclusions are drawn in the last section.

II. MILLIMETER-WAVE TECHNOLOGIES FOR PPDR

In this section, we elaborate on the utilization of mmWave systems in mission-aware PPDR scenarios. Particularly, we discuss the technology aspects of mmWave communications and identify the key challenges of using mmWave radios for PPDR.

A. FEATURES OF MILLIMETER-WAVE COMMUNICATIONS

The recent standardization activities behind 5G NR and WiGig systems are aiming to enable novel technology layout for real-time heavy-traffic applications, such as ultra-high definition video streaming [24], augmented and virtual reality (AR/VR) broadcasting [25], and proximate gaming [26], [27]. These solutions adequately address the bandwidth demands by utilizing the more abundant mmWave spectrum, primarily in 28, 60, and 73 GHz bands [28]–[30].

Radio propagation properties at mmWave frequencies are fundamentally different as compared to microwave setups. This is primarily due to the effects of link blockage, inherent directionality, and complex multi-path propagation, where various obstacles may occlude, reflect, or scatter the narrower mmWave beams [31]. The latter poses numerous challenges related to communication reliability and service continuity that need to be resolved comprehensively [17], [32]. The use of mmWave communications in indoor environments further complicates propagation because of multiple obstacles (e.g., walls, furniture, people) [33]–[35], which lead to more complex and dynamic propagation. In addition to blockage caused by other objects, there are *self-blockages* where a person blocks own links [36], [37].

The use of mobile access points, such as cells-on-wheels (CoWs, [38], [39]) and aerial access points (AAPs, [40], [41]), may enhance the performance of mmWave access technologies by maintaining line-of-sight (LoS) communications for users who are currently blocked or outside the base station coverage. However, these solutions are featured by relatively long deployment times and require additional resources, such as maintenance expenses for an unmanned aerial system. Hence, the use of such access points may not be suitable in all contexts.

To alleviate the effects of blockage and improve the reliability of mmWave connections, 3GPP has recently outlined multi-connectivity features [16]. Accordingly, a device may establish links to multiple access points (APs) in its proximity and dynamically change the serving AP if the current link experiences a blockage. Such an approach yields a dramatic decrease in the outage probability levels [19]. In the absence of network infrastructure, this concept can be enabled via device-to-device (D2D) communications [42], [43]. Direct connectivity between user devices allows for establishing a mesh network topology [44], which expands the service area of the mmWave APs. D2D-based mesh topologies naturally offer multi-connectivity opportunities for the partnering

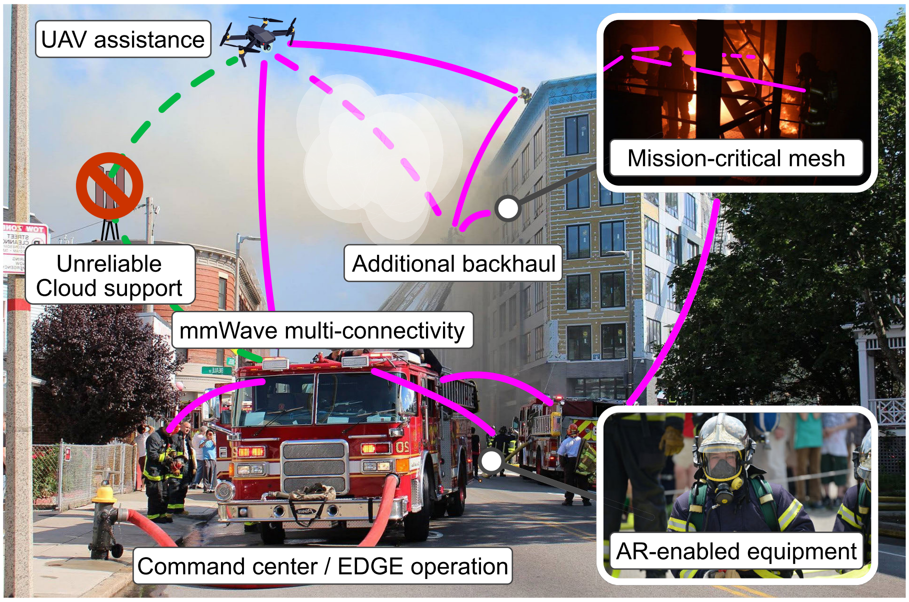

FIGURE 1. mmWave-enabled PPDR operation with a heavy-traffic application.

devices. Multi-connectivity naturally improves the resilience of a communications session to blockage because if a single link is occluded, the device can reroute its traffic via other connections.

In summary, it is known that link blockage may considerably limit the performance of mmWave-based systems. However, the situation can be notably improved with mobile APs arranged in a mesh topology.

B. PUBLIC PROTECTION SCENARIOS

Unexpected natural or human-made disasters require the safety agencies to always be prepared for PPDR situations in uncertain environments. The goal of PPDR missions is to reduce the risk to people's lives and property damage. Generally, a PPDR situation can be regarded as a multi-agent system comprising of intelligent entities, such as human rescuers and autonomous robots. Successful accomplishment of a PPDR mission hinges upon (i) continuous situational awareness, (ii) fast and reliable analysis of data and subsequent decision-making, and (iii) efficient coordination and cooperation between the rescue team members to eliminate task conflicts and duplication.

Innovative assisting technologies are extensively utilized to facilitate various PPDR missions. Computer vision systems have been proposed to obtain holistic information about the problem and its context for improved situational awareness [45]. These allow for monitoring the affected area in order to detect victims, assess damage, and evaluate hazards. The information analysis and decision-making processes can then be supported by AI-based applications, which may operate in a distributed or centralized manner [46]. Finally, dedicated radio technologies enable the coordination and cooperation inside the rescue team.

Previously, voice communications featured as the primary service supported by the PPDR systems. These are now expected to facilitate multiple additional applications that integrate voice, data, video, and image transmission as part of their multimedia capability to enable smooth coordination [47]. The latter requires more throughput and thus higher frequency bands where sufficient spectrum is available. Hence, mmWave communications technologies operating over the rich amounts of bandwidth can presently be considered as the key enabler for the emerging multimedia-ready PPDR applications.

C. APPLYING mmWave TECHNOLOGIES FOR PPDR

In addition to link throughput, there are further specific requirements pertaining to contemporary PPDR communications technologies [47]. Notably, those need to provide uninterrupted services irrespective of the current availability of the static network infrastructure. As long as cellular connectivity remains operational, PPDR applications can also exploit it.

Alternatively, other means of communication have to be deployed, e.g., in tunnels, inside buildings, or wherever the network infrastructure has (partially) collapsed [48]. These may rely on proximity-based D2D mesh operation, see Fig. 1, wherein the devices acting in close proximity (within the reach of a short-range wireless radio) may initialize direct links instead of utilizing network infrastructure. Therefore, the load on the cellular network may decrease, the operation without it might become possible, and better energy efficiency can be achieved. Therefore, the use of proximity-based direct communications is one of the promising solutions for beyond-5G connectivity.

Mesh-based mmWave solutions are expected to be utilized in collaborative PPDR missions to ensure robust connectivity between the rescue team members and enable traffic-hungry applications even when the cellular infrastructure is unavailable [49]. However, the use of advanced mmWave mesh topologies introduces additional challenges that relate to complex blockage dynamics [50]. Indeed, PPDR applications are expected to operate in hazardous environments, which may affect the propagation of mmWave beams. Furthermore, the context of the PPDR mission itself may deteriorate the radio conditions.

As a result, the mmWave mesh system reliability in PPDR situations depends on the mission type as well as on multiple environmental factors. Based on that, it is essential to not only provide high capacity during PPDR operation but also to develop reliable connectivity mechanisms and ensure resilience to various environmental conditions in mmWave-based mesh systems.

III. AI-AIDED MILLIMETER-WAVE MESH SYSTEMS

In this section, we discuss the application of AI methods in the context of mmWave mesh operation. We begin with a brief introduction and then review the use of AI in self-organizing mesh systems. Finally, we conceptualize AI-aided blockage prediction for a mmWave PPDR mesh.

A. DIVERSITY OF AI METHODS

AI techniques have entirely changed human life, from home appliances to automobiles, where every device or a piece of machinery is using some sort of an AI method. Since the beginning of AI evolution, researchers have introduced many AI practices including knowledge representation, expert systems, machine learning, neural networks, multi-agent systems, genetic algorithms, fuzzy logic, neuro-fuzzy, etc. However, based on the state-of-the-art achievements by machine learning and neural networks-based methods, most of today's AI techniques belong to either of the three major types: supervised, unsupervised, or reinforcement learning [51].

The former addresses the problems relying on labeled data (ground truth) or prior knowledge about the expected output. Typically, these tools are used in the context of classification and regression. In classification, the output is acquired in the form of labels or discrete values, whereas in regression, it is obtained as continuous values. Supervised learning algorithms include neural networks, convolutional neural networks, support vector machines, decision trees, naive Bayes, and linear regression. These techniques are widely applicable in many areas including object detection, pattern recognition, speech analysis, human activity recognition, and bio-informatics [52]–[54].

Unsupervised learning methods deal with the problems having unlabeled data, i.e., input with no corresponding output [55]. These automatically establish various patterns in the input data to learn its structure and make decisions based on similar patterns. Most of the corresponding algorithms are used for clustering, association rule learning, and data compression/generation in autoencoders. The typical unsupervised learning algorithms are K-means clustering and principal component analysis. Unsupervised learning tools are widely used for image segmentation, anomaly detection, and association mining.

Reinforcement learning employs reverse dynamics, such as reward and punishment to "reinforce" the knowledge for learning [56]. Unlike classical approaches, reinforcement learning exploits the concept of interacting with the environment based on trial and error. In reinforcement learning, the problem can be solved by performing two types of tasks, continuous and episodic. Continuous tasks persist (like forex/stock trading), while episodic tasks have the starting and ending points, which delimit an episode (like playing a game to complete a mission and move to the next level). The well-known algorithms of reinforcement learning are Q-Learning and State-Action-Reward-State-Action (SARSA, [57]). The reinforcement learning algorithms are widely utilized in robotics, web system configuration, advertising, and gaming.

B. AI IN SELF-ORGANIZING NETWORKS

"Brains exist because of the distribution of resources necessary for survival and the hazards that threaten survival vary in space and time" [58]. This statement is equally applicable to AI used in self-organizing networks since the very utilization of AI aims at efficient management of resources and avoidance of hazards. Here, the role of resources is featured by connectivity and throughput, whereas blockage, interference, and technological incompatibility between the nodes of a mesh can be interpreted as hazards.

The three major sub-functional groups of AI for the emerging mesh networks are self-configuration, self-optimization, and self-healing [59]. The former is required to enable network association simplicity regardless of the employed radio interface or device capabilities. During the configuration stage, the network needs to invoke an authentication procedure and set up the radio interfaces of its nodes, e.g., transmit power, data, and control plane protocols. In the context of self-configuration, the AI can be used for recognizing new users, configuring wireless interfaces, predicting events when the current network state changes, etc.

Mesh networks are highly dynamic systems; hence, their management has to be adaptive, enabled by continuous self-optimization. This includes monitoring of the network state and subsequent adjustment of the network and interface parameters to reach high efficiency of resource utilization. Self-optimization covers a number of aspects including power efficiency, mobility of users, quality of links, and traffic dynamics. It may be empowered by the AI methods, which are utilized for the prediction of user mobility by choosing reliable connections between the nodes of a mesh, predicting link quality and traffic flow structure based on previous experience, and tracing network users. Due to AI, the network may reduce the risk of failures and wastage of resources. As a result, the quality of user experience becomes higher. Hence, self-optimization aims to enable low latency, high bandwidth,

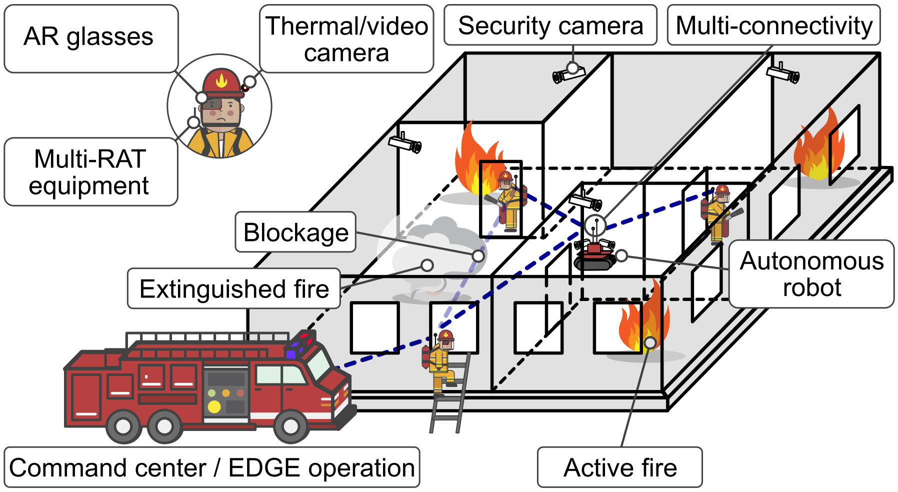

FIGURE 2. **Multi-connectivity mmWave mesh setup of interest.**

and better connectivity within a mesh network with higher degrees of temporal and spatial variation in user demands.

Self-healing of a network is related to recovering its functionality after failures. With respect to mesh systems, a failure can be defined as a state of the network where communications between two or more nodes is interrupted. A significant proportion of such failures is caused by a lack of connectivity between the devices. The AI methods used for self-healing aim to mitigate the failure events and automatically recover the network performance [59]. They may include but are not limited to automatic failure detection and diagnostics, reconfiguration of nodes in real-time (e.g., increased transmit power to extend coverage of certain nodes), and rerouting. In severe cases (e.g., an essential link is faulty), the original network can split into two or more isolated parts.

C. USING AI FOR BLOCKAGE PREDICTION

Dissimilar static and dynamic objects (e.g., people, buildings, vehicles) may cause link blockage in mmWave mesh systems, which are thus characterized by a high degree of temporal and spatial variability. The objects in question may not only occlude the direct path but also block the reflected paths by disrupting communications between the nodes of a mesh for prohibitive periods of time. As a result, the performance of PPDR applications utilizing mmWave mesh capabilities may degrade considerably.

Recent developments in AI techniques are capable of anticipating the blockage situations in mmWave mesh networks. Particularly, AI-based algorithms may employ computer vision and sensory data to acquire the indicators of an imminent blockage. For example, AI-aided systems can predict link occlusions caused by people or static objects (such as trees, buildings, and landscape) by utilizing the data about (i) their trajectory and speed, (ii) trajectory and speed of the mmWave mesh nodes, and (iii) location of static obstacles.

The blockage prediction systems are potentially able to improve the sustainability of a mmWave mesh layout. If the latter is made aware of a probable blockage, the loss of the radio connectivity can be prevented by relocating the nodes or resorting to D2D technologies, such as peer relaying. Moreover, reliance upon blockage prediction mechanisms potentially requires fewer resources as compared to the use of assisting technologies, such as COWs and AAPs. Hence, AI-enabled blockage prediction can become an attractive solution for improving communications reliability in mmWave mesh systems.

IV. AN ILLUSTRATIVE SCENARIO

In this section, we consider a fire suppression mission as an illustrative example to assess the gains from the use of the AI-aided blockage prediction in mmWave mesh systems.

A. FIRE SUPPRESSION MISSIONS

In the addressed scenario, we assume that a fire spreads dynamically in a particular area of interest, while the involved firefighters lack awareness about the spots of fire across this area, see Fig. 2.

To enhance the efficiency of a fire suppression mission, the collaborating team members may employ AR-based applications [60] and advanced sensory equipment, which require high throughput and network availability to support effective teamwork. The team is also supplemented by autonomous robots aiming to improve the probability of mission success. The said devices utilize multiple cameras and sensors to detect fire and determine their appropriate locations for serving as relay nodes for communicating with a potentially blocked device (if such locations exist), and move in the selected direction. The media-related equipment relies on 3D HD 360° video streaming, which requires approximately 100 Mbit/s of bandwidth per user [61] for the upload link (toward the processing server).

Moreover, about 5 Mbit/s may be demanded by the advanced sensory systems, including on-body health monitoring devices, sensitive smoke analysis sensors (for recognizing which materials are burning), thermal sensors, etc. Additionally, an AR-based assisting application may require up to 15 Mbit/s, e.g., for building navigation, environmental awareness, and command center notifications. In total, the utilized applications call for about 120 Mbit/s of bandwidth per one user. These demands are expected to be satisfied by a mmWave proximity-based mesh system. The latter is maintained between all of the participants of the firefighting team. The information transfer between the remote nodes and the gateway is multi-hop. To improve the reliability of this network, each participant supports multi-connectivity of M simultaneous links to its neighbors, referred to as the ''degree of multi-connectivity''. Further, if/when all M links are blocked, the network management layer may employ robot-based relays to establish alternative data routes.

A characteristic feature of the considered scenario is dynamic link blockage caused by water vapor from the fire extinguishing process. Recent AI methods may detect the fire by using video cameras, e.g., a video surveillance system deployed in the area and wearable video cameras of the firefighting team members. Knowing the exact location of the fire, the considered system becomes more aware of the spots where connectivity disruption chances are high. Using this information, the mesh network can improve its reliability by establishing an alternative connection proactively.

B. AI FOR DYNAMIC BLOCKAGE DETECTION

Accidents involving fire directed the attention of researchers to the development of new fire detection systems [62]. Presently, these follow either of the two general approaches: traditional and vision-based detection. Traditional fire detection systems utilize sensors, which rely upon temperature measurements, particle sampling, smoke analysis, and relative humidity sampling [63]. However, these sensors are mostly applicable for indoor environments, and remain unable to provide required details about the fire (e.g., burning degree, location, size). Vision-based systems utilize computer vision techniques and can overcome the limitations of the traditional systems [64], [65].

Recently, vision-based systems attracted significant research attention in the field of early fire detection due to their efficient response. These systems are attractive due to various advantages including (i) larger covered regions, (ii) lower costs, (iii) detection of fire without visiting the scene, (iv) providing the fire details such as location, burning degree, and size. Due to these features, vision-based systems may significantly enhance the efficiency of the traditional fire alarm applications.

The vision-based systems rely on static or adaptive (learned) methods for fire recognition purposes. The methods belonging to the first category use color and shape features for detecting the flame on an image (e.g., RGB, HIS, YUV, YUC, and YCbCr models). The main drawback of these methods is in their high false alarm rate [66]. Several tools based on motion features were developed to cope with this issue. However, these solutions are limited to shorter distances. Adaptive methods rely on convolutional neural networks (CNNs) for efficient fire detection [67]. The CNN-based approach enables fire detection over longer distances and with higher accuracy.

CNN is one of the essential types of neural networks initially designed for 2D image data, but presently its variants can also handle 1D and 3D data. A CNN is typically composed of convolutional, pooling, activation, and fully connected layers that are stacked in a hierarchical way. The convolutional and fully connected layers contain a number of kernels that are also known as neurons or trainable parameters, while the pooling and activation layers are functions without trainable parameters [68]. The parameters of these layers are learned via backpropagation techniques over numerous iterations to fit a particular task.

The convolution is a linear operation, which convolves a kernel over the entire image to extract the needed patterns from it. The pooling layer of a CNN is responsible for reducing the dimensionality of features. The success of the CNNs is not only in the field of object detection and image classification, but also in more complex problems, such as smoke and fire scene analysis [69]–[71], image, and video retrieval, medical image analysis, action, and activity recognition [72], scene parsing, and movie analysis [73]. Over the past few years, CNN-based methods became popular for feature extraction from videos as well as the image data. Moreover, the feature extraction techniques confirmed that the initial layers of a CNN may extract local image features, while its deeper layers provide a global representation of the image data.

In this paper, we focus on the CNNs that demonstrate state-of-the-art performance in image classification and other computer vision tasks. CNNs are deep learning frameworks that are inspired by the mechanism of visual perception of living creatures [74]. Their application in fire detection systems will substantially improve the detection accuracy, which will eventually minimize fire damage while reducing the ecological and social consequences. However, a major concern related to CNN-based fire detection systems is their implementation in the real-world surveillance networks due to the high memory and computation requirements for inference.

We further advocate the use of proactive approaches to avoid blockage situations in PPDR environments by assuming that AI is utilized to detect fire locations and provide information about a potential blockage situation that may occur in the future. When the fire location is detected, the multi-connectivity mmWave functionality is employed to avoid link blockage. Two potential situations are considered. If there are other connections available at a node whose link is going to be occluded soon, the traffic is rerouted via these alternative connections. If the node in question does not have backup connections to other nodes, a robot (if there is one available) is steered to establish a backup connection for the considered node. Otherwise, if the link quality is deteriorated due to blockage, the subject node becomes disconnected from the network. We assess these options below.

To this aim, we conduct a performance evaluation campaign based on two datasets. The first one comprises of a relatively small number of 226 photos, where 119 are with fire and 107 are without [74]. The second one is more informative and corresponds to 31 videos captured in both indoor and outdoor environments, where 14 videos contain fire and 17 videos belong to the non-fire class [70]. These sets were selected specifically with respect to two scenarios: (i) low-quality connection (the first set where the frames are delivered to the CNN with low rate of around 2 FPS assuming poor link quality), and (ii) high-throughput connection potentially provided by the mmWave links (the second set where FPS equals 25 for any resolution).

We further apply our pre-trained GoogleNet algorithm to both sets and calculate the false alarm rate (FAR) as well as the accuracy for both datasets under different resolution constraints (from 640 $\times$ 480 to 4K quality). Our results indicate that for the small and infrequent frame rate of the first dataset the accuracy is kept approximately at the level of 89%, while the FAR value fluctuates around 18% even when utilizing the CNN. When the overall system is operating with higher FPS and/or resolution, e.g., utilizing mmWave connections, the accuracy reaches 98.5% and FAR drops to near zero.

C. METHODOLOGY AND SIMULATOR DESCRIPTION

Our approach is based on a computationally efficient CNN implementation inspired by GoogleNet architecture, with its reasonable computational complexity and suitability for the intended problem as compared to other computationally expensive networks, such as AlexNet. It is utilized for fire and blockage detection, localization, and semantic understanding of the scene of the fire. This solution is based on a paradigm that classifies the input video frames into their respective class, i.e., "Fire" and "Non-Fire".

For the classification of videos, we employ a pre-trained GoogleNet architecture with further modifications according to our target problem. A simplified algorithm for fire detection utilized in the proposed solution is shown in Fig. 3. There are several reasons behind preferring this option for the detection of fire in our illustrative use case. The first one is in its high performance during fire detection. The second reason is the small size of the model, which allows for deploying the system on resource-constrained edge/fog devices. Finally, the proposed solution outperforms other state-of-the-art CNN models and fire detection methods in terms of its FAR rate and accuracy [70].

The proposed system includes two network overlays that function cooperatively. The first one utilizes mmWave radio technology for enabling high throughput among the users, which is required for the heavy traffic of media-centric applications. The second overlay relies upon a long-distance wireless technology (IEEE 802.11ah nicknamed Wi-Fi HaLow), which provides reliable albeit low throughput connections among all the nodes of a network [75]. These low throughput connections carry signaling for managing the mmWave mesh operation.

The proposed system operation comprises of continuously repeating cycles as shown in Fig. 4. Repeating the cycle allows for timely updates of the information about the mmWave mesh status. The frequency of updates depends on the operation dynamics as regulated by the command center. Such dynamics includes the number and density of nodes in the network, the intensity of blockage situations, etc. Scenarios with higher levels of dynamics require a higher frequency of updates. Every update cycle starts by determining the current topology of the mmWave mesh.

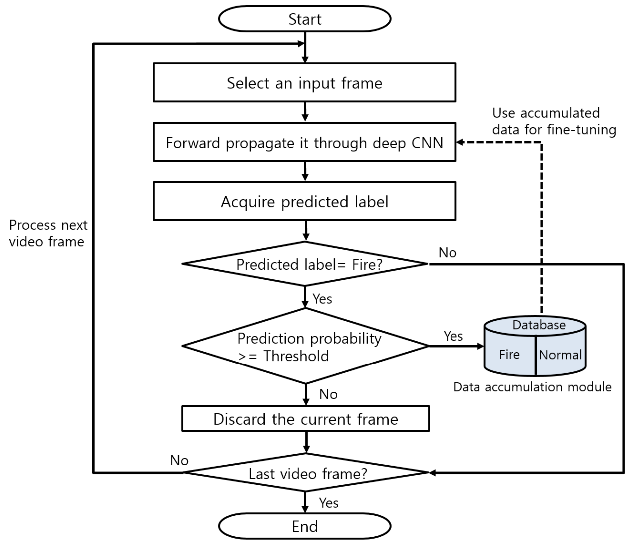

FIGURE 3. Simplified algorithm for efficient fire detection.

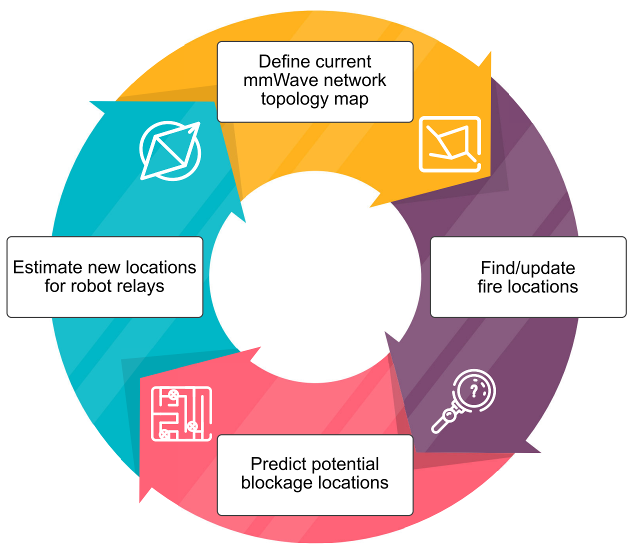

FIGURE 4. System operation cycle.

For this purpose, every node sends its coordinates and mmWave link-state advertisements (LSAs) via the long-range HaLow connections. Using LSAs, a processing unit located in the command center acquires the current mmWave mesh topology. At the same time, the command center recognizes the fire zones and updates their locations by utilizing the available media and sensory information obtained from the fire suppression team members via the mmWave mesh. At the next step, the system provides a mapping of the fire locations, the building plan, and the mesh topology to predict the potential blockages as illustrated in Fig. 5. Finally, using the information about the potential blockages, the system estimates where to move the robot relays for reducing the risk of disconnecting mesh nodes from the gateway.

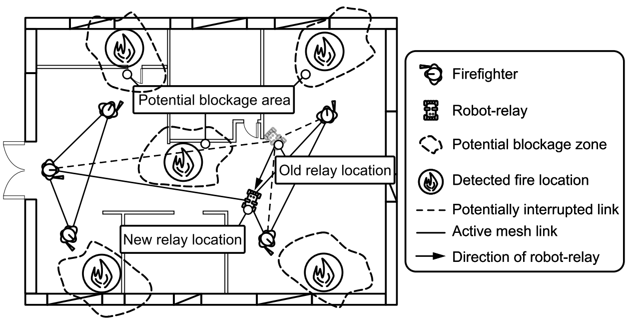

FIGURE 5. Blockage prediction scenario: top view.

For the numerical assessment, we employ our advanced "large-scale" system-level simulator (SLS), which takes into account all of the relevant details of the mmWave system operation and has been thoroughly calibrated in our past publications [20], [76]–[81]. This SLS tool is capable of mimicking large-scale environments together with the underlying wireless technologies, such as LTE, WiFi, and mmWave-based RATs: IEEE 802.11ad and 3GPP NR.

The tool is based on a flexible event-driven architecture, which allows decreasing the computation time in the low-load scenarios. For all the considered technologies, PHY and MAC layers are implemented in detail, based on the appropriate IEEE and 3GPP specifications, whereas the higher layers are generally simplified to abstract away the traffic models represented by analytical approximations. Regarding the environment generation, our SLS tool supports 3D geographical models, which take into account time- and location-based interference, antenna configurations, and UE mobility models.

With respect to mmWave communications, the SLS implements the propagation models specified by 3GPP in [82], with dynamic blockage extensions from [80], [81] and further advanced functions, such as multi-connectivity [16]. The D2D and multi-hop functionalities in mmWave bands are currently under specification by both IEEE and 3GPP for WiGig and NR technologies (under IEEE 802.11ay and 5G NR standards, respectively). Hence, to assess the performance of multi-hop relaying solutions, we rely on the current work-in-progress 3GPP documents (R1-1812199, R1-1812982, and R1-1813418), along with the NR relaying capabilities discussed in TR 38.874 – initially planned for Rel. 15 and now continued with the focus on Rel. 16. An open-source version of our SLS is made available at [83].

D. RELIABILITY ASSESSMENT OF AI-AIDED MESH

We consider an area of 100 × 100 m with 10 fire crew members, each equipped with mmWave-based radios for communications and cameras for video streaming. The crew is accompanied by K autonomous robots also supplied with mmWave radios and cameras suitable for 4K video transmission. A mesh network is constructed between the firefighting crew members to enable uninterrupted video delivery to the remote cloud. In order to capture the dynamics of the fire suppression process, we employ a spatially-temporal Poisson process [84] that is built on three parameters: (i) the temporal intensity of fire locations, (ii) the mean duration of evaporated water after the fire suppression, and (iii) the radius of the evaporated water. As confirmed by the measurements in [85], attenuation caused by water is sufficient to occlude the propagation of mmWave signals.

To improve the system performance in dynamic blockage-prone environments, devices carried by the crew members implement multi-connectivity functionality; hence, they establish multiple links to the neighboring nodes and switch over to non-blocked connections whenever the current link is disrupted. The considered mmWave technology is IEEE 802.11ay operating in the 60 GHz band [11]. To approximate the coverage of a single mmWave radio, we utilize the InH propagation model and 0.2 W of transmit power [82]. Other system parameters are summarized in Table 1. We specifically note that as compared to

TABLE 1. Default system parameters.

Parameter	Value
Operating frequency, f_c	28 GHz
Antenna array	16 × 16 el. (planar array)
Channel model	3GPP InH
Transmit power	0.2 W
Area of interest	100×100 m
Number of static blockers	10
Radius of static blockers	5 m
Attenuation by static blockers	40 dB
Temporal intensity of fire locations	0.1 events/s
Mean duration of suppressed fire location	120 s
Radius of suppressed fire location	3 m
Attenuation by suppressed fire location	20 dB
Number of firefighting crew members	$\{10, 20, 50\}$
Moving speed of crew members	3 m/s
Mobility model of crew members	Random direction model
Number of autonomous robots	$\{1, 2 \dots 10\}$
Number of simultaneously supported links	$\{1, 2 \dots 10\}$
Number of executions per setup	10e5

microwave technology, user devices greatly benefit from operating in the mmWave band. In particular, having 16×16 linear antenna arrays leads to approximately 6.5° half-power beamwidth (HBPW) at both the transmit and the receive ends.

Further, we evaluate and compare two representative scenarios. In the *baseline* setup, no fire detection assistance is provided, and the firefighting crew members move randomly across the area of interest at the speed of v in their search of a fire location for suppression. Note that the baseline scenario includes the state-of-the-art blockage avoidance techniques, such as multi-connectivity [86] – the devices are allowed to support multiple links to improve network connectivity. In the *AI-aided* scenario, fire detection capabilities are used to guide the firefighters toward the actual fire locations. To improve the levels of connectivity, in addition to supporting multiple simultaneous links, devices may rely on a fleet of autonomous robots moving in the environment with the speed of v_R. The AI algorithms not only allow to detect the locations of fire but also employ cameras for predicting the blockage situations. If a blockage is expected to occur, the respective crew member connects to an autonomous robot, whose aim is to support additional relay links to maintain uninterrupted connectivity.

For the *baseline* and the *AI-aided* scenarios, we consider the following performance metrics related to mmWave system reliability in dynamic blockage environments: (i) fraction of time when a randomly chosen node in the mesh is disconnected, (ii) probability that a certain number of nodes are disconnected at a randomly chosen instant of time, (iii) intensity of node disconnections from the mesh, and (iv) data rate at the access gateway. Note that these parameters depend on the considered setup, e.g., the number of nodes, the degree of multi-connectivity, the use of AI-based proactive blockage detection, and the number of autonomous robots. A system-level performance assessment is then conducted within our simulation environment that integrates the main functionality of the mmWave system and extends it to support the multi-connectivity operation. The core of this modeler is based on a discrete-even simulation framework. The statistics were collected via the method of replications in the steady-state period. The beginning of this period was determined with an exponentially-weighted moving average (EWMA) filter [87].

First, in Fig. 6 we study the fraction of time an arbitrarily chosen node is disconnected from the network for both scenarios of interest as a function of the temporal intensity of fire locations. Analyzing these results, one may observe that the spatial diversity made available via multi-connectivity allows to drastically reduce the parameter under investigation over the entire range of considered intensities. However, the use of AI for fire detection and autonomous robot relaying results in even more profound positive effects. Particularly, the system with the multi-connectivity degree of 3 and no AI support performs worse than the system with AI assistance and $M = 1$. The use of multi-connectivity and AI together allows to dramatically improve the performance by efficiently avoiding blockage even in extremely dynamic conditions where the fire location intensity reaches significant values of $0.4 - 0.5$ events/s.

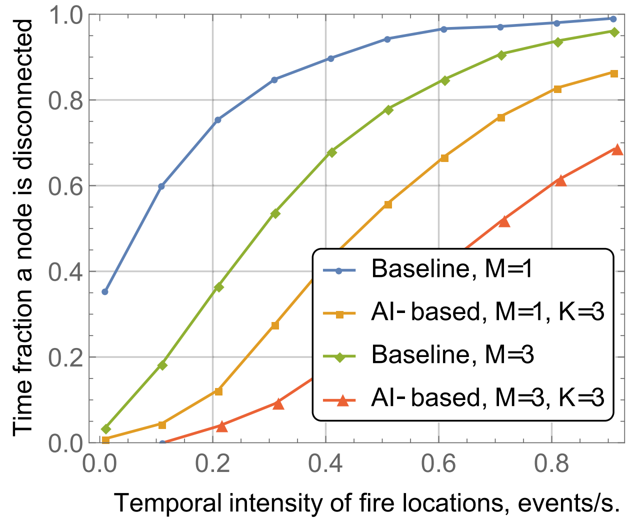

FIGURE 6. Fraction of disconnect time from a mesh.

Another parameter of interest that characterizes the reliability of a mesh is the number of disconnected nodes at an arbitrarily chosen instant of time. Recall that this value characterizes the ability of the network to support the ongoing mission. Here, the more nodes are disconnected, the less information is available for coordinating a mission, which may eventually lead to additional nodes disconnecting from the network. Fig. 7 illustrates this behavior for the degree of multi-connectivity $M = 3$ and the temporal intensity of fire locations of 0.1 events/s as a function of the mean water vapor duration in the suppressed fire locations for both scenarios. As one may observe, the effect of AI assistance is visible across the entire considered range of the mean durations of the suppressed fire location. For $M = 3$ and $K = 6$,

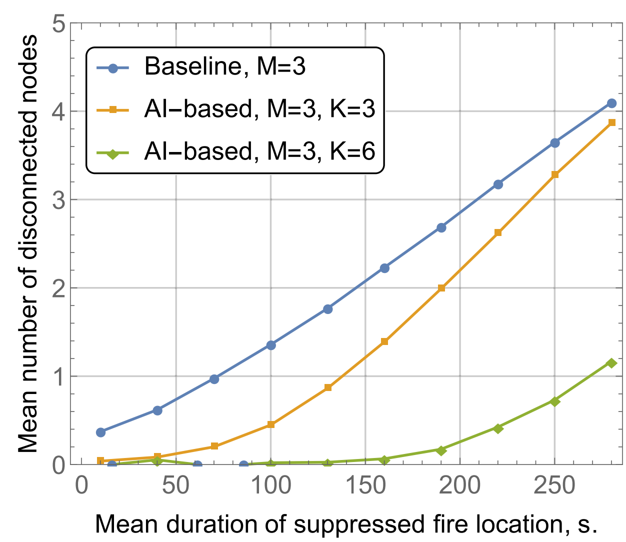

FIGURE 7. Mean number of disconnected nodes.

the mean number of disconnected nodes remains close to zero for up to the duration of approximately 150 s. However, as the mean duration increases, the system is no longer capable of maintaining uninterrupted mesh connectivity even with the autonomous robot relays, and the mean number of disconnected nodes increases.

We further characterize time-dependent performance – the intensity of node disconnections from a mesh in Fig. 8 as a function of the degree of multi-connectivity, M, the number of autonomous robot relays, K, and the mean water vapor duration in suppressed fire locations, $1/\theta$. As we learn, the response of the system is qualitatively similar for both the baseline and the AI-aided scenarios. An initial increase in the intensity of node disconnections is explained by the fact that the temporal intensity of node locations adds to the blockage dynamics as moving firefighters begin to experience link interruptions more frequently. However, when the intensity of dynamic blockers exceeds a certain value that generally depends on the type of the scenario and the selected system parameters, the intensity of node disconnections begins to decrease. The reason is that in this regime the number of static and dynamic blockers becomes so high that individual blockage periods merge into the longer ones, thus forcing a node to spend more time in the disconnected state, see Fig. 6.

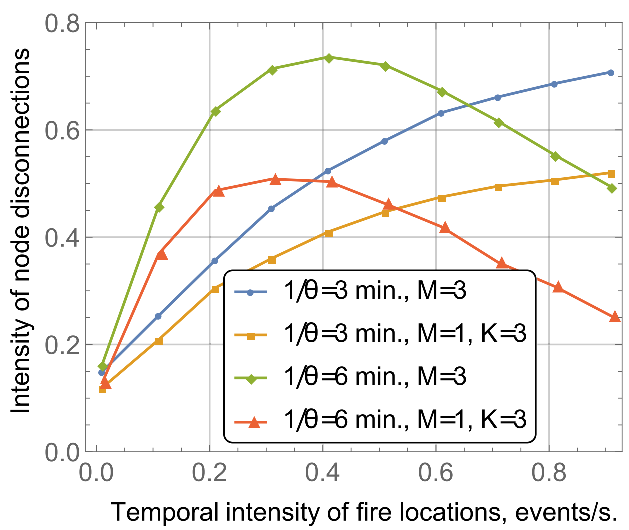

FIGURE 8. Intensity of node disconnections from a mesh.

Finally, in Fig. 9 we assess the maximum aggregate data rate of the mesh network at the access gateway for $M = 3$ and $K = 3$. Observe that an upper bound on the radio access level data rate is provided by a zero intensity of fire locations, which results in approximately 5.4, 3.7, and 2.0 Gbps for $N = 50$, $N = 20$, and $N = 10$, respectively. These values can be used for choosing the appropriate mmWave technology in the overlay. Particularly, the IEEE 802.11ad solution theoretically provides up to 6 Gbps and may thus support the fire suppression crews of up to 50 persons. For higher values of N, the emerging IEEE 802.11ay technology can be preferred.

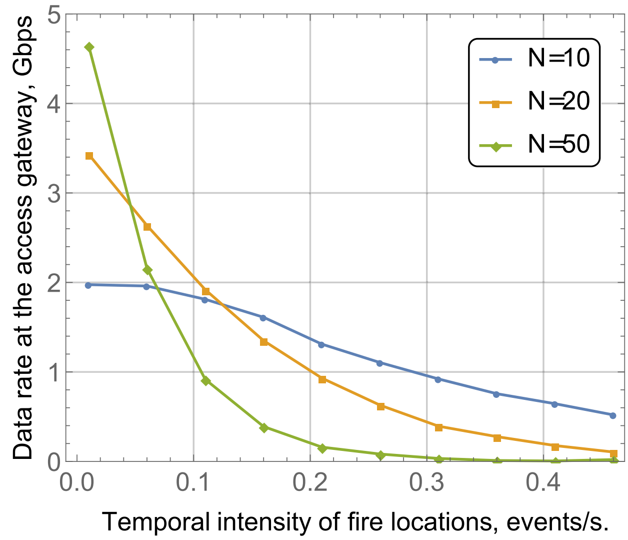

FIGURE 9. Data rate at the access gateway.

One may also notice that for all the values of N, the data rate decreases as the temporal intensity of fire locations grows. The reason is that the time fraction when a node is disconnected from the network rapidly increases, as shown in Fig. 6, which reduces the number of nodes delivering their traffic to the gateway. This process is characterized by an avalanche-like trend, since a lower fraction of the delivered data leads to fewer fire locations detected, which, in its turn, increases the fraction of disconnect time. Hence, for all the values of N, the data rate drops to zero. In this regime, the system no longer maintains its intended functionality, and additional robot relays are needed for improved mesh operation.

V. CONCLUSION

The contemporary PPDR requirements go far beyond conventional voice services. The use of advanced applications like AR/VR may drastically improve the efficiency of collaborative PPDR missions by providing real-time 3D information about the environmental conditions. These new requirements naturally call for the use of mmWave radio technologies that offer extensive bandwidths at the air interface. To maintain uninterrupted connectivity of mmWave-based mesh layouts in challenging environments with both natural and artificial obstacles, one has to rely upon advanced techniques to intelligently predict the potential blockage situations and effectively mitigate them in real-time.

In this work, we considered the use of AI-aided techniques to improve the performance of the mmWave-based mesh systems in the representative firefighting scenarios. We employed computer vision to detect the areas with potential blockage situations and further predict the chances of losing connectivity in dynamic self-organizing mmWave deployments. In this case, either the user itself or a remote control center may take preventive measures to avoid potential node disconnects by, e.g., utilizing proximate robot-based relaying. Our numerical results indicate that the proposed approach significantly enhances the reliability of the mmWave mesh operation by substantially reducing the fraction of disconnect time.

The results of this study are relevant beyond the considered fire suppression scenarios. Particularly, AI-based solutions can be utilized for predicting blockage situations in 5G NR systems by improving link reliability and thus augmenting session continuity.

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