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Cognitive Communications System for Ultra-Low Size, Weight and Power (SWAP) Attributable Platforms

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ABSTRACT Communications resiliency and data distribution assurance has been compromised in highly competitive, dynamic, and stressing environments with the introduction of off the shelf, high performing jammers. This paper introduces a novel cognitive communications system that can be fielded on small attributable platforms; the architecture amalgamates a highly capable environmentally perceptive aperture, a software defined radio, and sophisticated networking techniques. The proposed cognitive communications system uses the 5G new radio waveform and applies groundbreaking machine learning methods to facilitate systems orchestration amongst its subsystems to transfer information effectively between nodes, and across large-scale multi-hop networks, essential for rapid strike missions. With the challenges imposed by mature and readily available jammers, a cognitive communications system can be used to maintain and sustain continuous communications to provide near real-time surveillance and situational awareness updates. In addition to describing the comprehensive cognitive communications system architecture, a jamming analysis will be presented. Performance results for an operational use case will be compared to existing trite architectures consisting of siloed apertures and standard radio systems to demonstrate an improvement of approximately 10 dB in communications margin with the auspicious technology offering of the cognitive communications system for low size, weight, and power attributable platforms.

INDEX TERMS Advanced networking, anti-jam, aperture, attributables, cognitive, communications, drones, machine learning, neural networks, unmanned systems, 5G new radio.

I. INTRODUCTION

Robust communications can be achieved by exploiting spectral and spatial diversity with cultivated aperture technology, emerging dynamic spectrum access (DSA) capable radios, and advanced networking solutions that enable connectivity and interoperability for large-scale, multi-hop networks. Key to communications resiliency is the assurance of data delivery by providing reach-back and data distribution to commanders outside of enemy lines. Small attributable platforms, such as mini-drones, are promising vehicles to serve as communications relays to provide increased intelligence, surveillance and reconnaissance to decision makers at the forefront of the battlefield. More recently, small attributable platforms are replacing locally distributed soldiers near adversaries [1] due to increased communications and weapons capabilities, thereby reducing probability of blue force peril [2]. In [3] maintaining small attributables cooperation and control is presented where the lack of efficient networking schemas that can manage communications in rapidly changing environments are identified as key challenges. [4] describes inherent problems of network management of such attributable systems as being time consuming and complicated, thus causing interoperability issues. Suggested technologies such as software defined networking (SDN) and network function virtualization (NFV) may be valuable in overcoming some of these challenges to provide ubiquitous connectivity to wireless devices in the future. SDN introduces a separation of the control and data planes, where the control plane performs the logical processing to include network management, and the

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TABLE 1. Comms relay platform & payload requirements.

Category	Requirement	Metric
Platform	Fuselage Length	73”
	Fuselage Width	8”
	Height	9”
	Weight	<100 lbs
Payload	Available Power	300 Watts
	Volume (Max)	975 in^3
	Weight (Max)	30 lbs

data plane delivers the packets to the appropriate interfaces. The separation of these two planes allows for the routing of traffic intelligently to exploit available network resources [5]. NFV, on the other hand, enables providers to establish many isolated virtual systems while sharing their physical systems [6]. While the introduction of different engineered network topologies for attributable-capable platforms is imminent, for example, as with microcosm swarm topologies, we propose to use a cognitive communications system (CCS) architecture that conducts cutting-edge systems orchestration between its three segregated subsystems to optimize data distribution and delivery amongst network participants while operating the 5G new radio (NR) waveform.

The 5G NR initiative uses modulation, waveforms, and access technologies that enable the communications system to meet the demands of high data rate services at low latencies. The waveform format of 5G NR is based on Orthogonal Frequency Division Multiplexing (OFDM) and Discrete Fourier Transform spread OFDM (DFT-s-OFDM) with adaptive modulation including Quadrature Phase Shift Keying (QPSK), 16 Quadrature Amplitude Modulation (QAM), 64QAM, and 256QAM. OFDM gives a respectable spectral efficiency whilst providing resilience to selective fading and enabling multiple access capability to be implemented using OFDM access (OFDMA) [7].

In this paper, small attributable platform requirements for hosting communications payloads are described. Also, the innovative CCS architecture which utilizes high-level systems operations to improve communications between nodes is outlined. Machine learning techniques are employed within each subsystem to predict aperture and networking behaviors that influence the way decisions are made to optimize information exchanges. Finally, a jamming analysis is presented to demonstrate the effectiveness of the CCS architecture when exercising the 5G NR waveform in its operationally deployed state. The analysis will be compared to legacy radio systems which use commercially available technology to highlight the benefits of such a CCS framework.

II. PLATFORM & PAYLOAD REQUIREMENTS

Small attributable platforms are emerging as new vehicles that can enable a multitude of tasks (e.g., support of commercial disaster recovery operations including wild-fire communications relays with command centers, etc.). The design and constraint requirements for a medium size unmanned aerial vehicle (UAV) are presented in Table 1 as defined in [8].

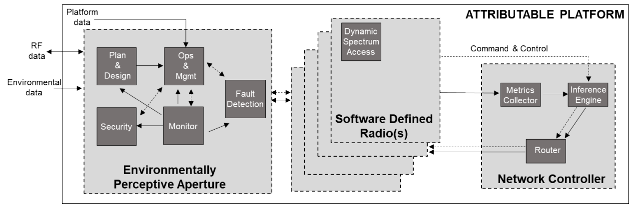

FIGURE 1. The cognitive communications systems hosted within the attributable platform provides machine learning influenced interactions to increase collaboration between the environmentally perceptive aperture, software defined radio(s), and network controller subsystems.

The payload size, weight, and power (SWAP) requirements are crucial metrics that need to be considered when designing the CCS architecture such that it can fit adequately within the bay of the platform, take advantage of platform power, and not exceed the maximum weight capacity, which would undoubtedly limit operations. In addition to the defined requirements above, the payload cost must be substantially low due to thousands of quantities needed for future unmanned military operations, such as surveillance activities. Also, these platforms would serve useful to be armed with advanced weaponry to support parallel strike missions if they successfully penetrated anti-access enemy territory.

While there may be hardware resource constraint challenges (or limitations) with implementing the proposed CCS architecture on the small attributable based on the payload requirements, the architecture itself is designed for modularity and scalability. The CCS architecture will be compliant with Open Mission Systems (OMS) where interfaces between software services and hardware subsystems will be standardized to allow data to be exchanged across those interfaces seamlessly. Additionally, with the implementation of standards, future capability expansions are possible.

III. COGNITIVE COMMUNICATIONS SYSTEM

The CCS architecture is depicted in Fig. 1; it consists of an environmentally perceptive aperture (EPA) subsystem [9], DSA capable software defined radio (SDR) subsystem, and a network controller (NC) subsystem [10].

Here, the wideband EPA functions in concert with an advanced SDR that can learn from its experiences over time to determine action and parameter selections to avoid interferences and operate in anticipation of connectivity challenges. The EPA subsystem can perform textbook beamforming, beam steering, and nulling by using learned experiences gained from interacting with the environment, and by having an introspective understanding of its own health and element status. The SDR is a powerful radio which comprises of a general-purpose processor used to perform signal processing, modulation and demodulation of the radio signals and can support different waveforms. The SDR is DSA aware, where the radio can effectively address spectrum scarcity challenges by sharing licensed frequency bands amongst users without any modifications to the radios or services in use [11]. The NC will use available quality of service (QoS) information, such as link capacity, throughput, latency, and packet delivery

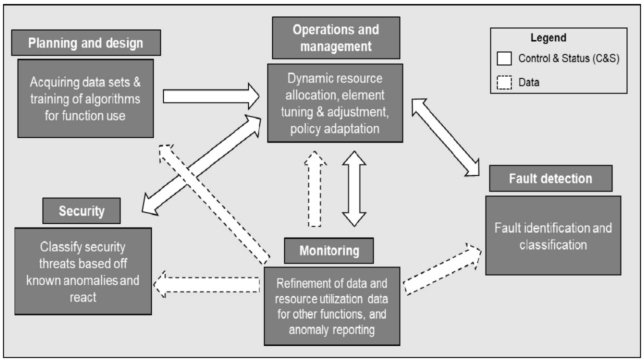

FIGURE 2. Functional sequencing consisting of novel machine learning techniques enable cognition required for an environmentally perceptive aperture.

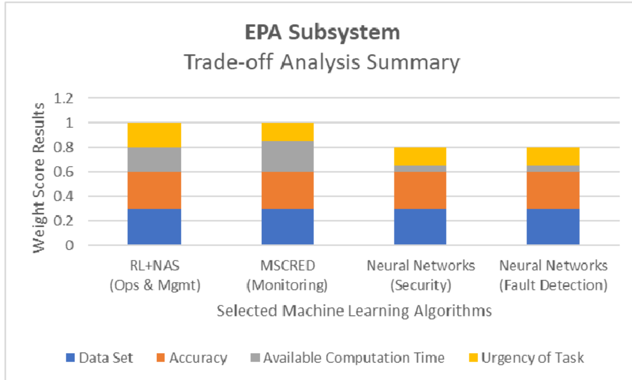

FIGURE 3. Complex trade-off analysis performed for machine learning methods to be used for antenna 'roles' suggests rationale for selection based on scoring of multiple criteria.

ratio provided from the SDR via proxy services, to support network route recommendations.

Furthermore, the CCS architecture applies machine learning to predict aperture and network behaviors under certain pre-trained conditions. The applied cognition improves link performance, interference mitigation, traffic routing, and therefore improves quality of experience (QoE) from an end user's perspective. Empowering communications with a robust, resilient CCS architecture will facilitate faster and more reliable data exchanges between the UAV platforms and executive leaders.

A. ENVIRONMENTALLY PERCEPTIVE APERTURE SUBSYSTEM

The EPA subsystem is composed of functional sequencing components built upon erudite machine learning techniques that perform designated functions or key roles as shown in Fig. 2. These roles are defined as planning and design, operations and management, monitoring, security, and fault detection. Here, planning and design will acquire data and train the functions for their intended operations prior to deployment. Operations and management function will implement a combination of deep deterministic policy gradient (DDPG) with neural architecture search (NAS) for vigorous, agile operations [12], [13]. Where the monitoring block will use multi-scale convolutional recurrent encoder-decoder (MSCRED) to tailor the data for other functional use (dimensionality reduction) and to detect anomalies [14]. Finally, both security and fault detection functional blocks will apply neural networks to classify known threats or systematic faults. With the growing complexity of current and future heterogeneous networks, advanced learning algorithms like the recommendations presented within this subsystem should be applied to optimize system performance. The EPA subsystem integrates with emerging SDR technology to learn from its experiences to overcome link performance challenges and interference mitigation, essential for the rapid expansion of small attributable platform communications.

Using systems engineering best practices, a trade-off analysis was conducted to evaluate which machine learning techniques would be best suited for each antenna function given the problem each function needed to solve. As a mechanism for differentiating between alternative solutions, a set of quantifiable selection criteria was chosen that includes data set (size, nature, and quality), accuracy, available computation time, and urgency of task to be performed. For a given set of criteria, not all of them are equally important in determining the overall value of an alternative for each function. Such differences in importance are considered by assigning each criterion a weighting factor that magnifies the contribution of the most critical criteria. For the purposes of this trade-off analysis, the subjective value method was implemented to apply a judgement of the relative utility of each criterion on a scale one through ten. This was derived specifically for contested communications application and may vary dependent on intended applications. The score assigned was then normalized using the linear maximization method for simple additive weight trade methodology using a benefit and cost criteria respectively. Results of the selected machine learning techniques for their quantifiable selection criteria for each function are summarized in Fig. 3.

B. SOFTWARE DEFINED RADIO SUBSYSTEM

The SDR subsystem will be DSA aware which will allow the radio to take advantage of RF sensing to gather and use spectrum situational awareness (SA) to dynamically select operational frequencies to transmit and receive communications on. This capability will run locally within each radio to swiftly recognize and resolve spectrum congestion and connect to previously undiscovered networks different available frequencies. Adaptation is constrained by knowledge of spectrum regulations that are loaded into the radio to ensure compliant operations.

C. NETWORK CONTROLLER SUBSYSTEM

The NC subsystem applies perception, learning, reasoning, memory, and adaptive approaches [15], and can proactively mitigate congestion using an inference engine. The inference engine contains both an oracle and a route filter capability. The inference engine acts as an expert model of the network traffic in a network, looking at time histories of traffic across

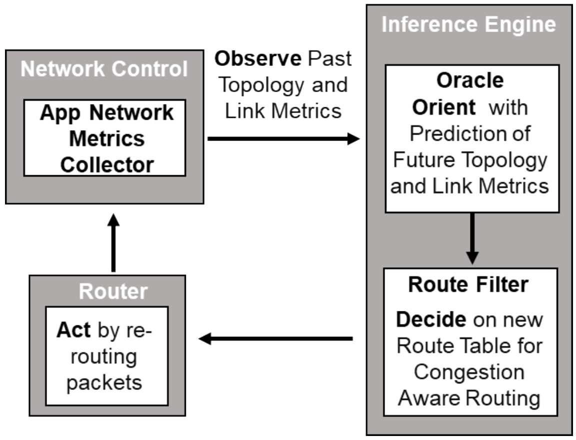

FIGURE 4. The Network Controller subsystem key tasks can be defined in terms of the observe, orient, decide, act (OODA) loop framework.

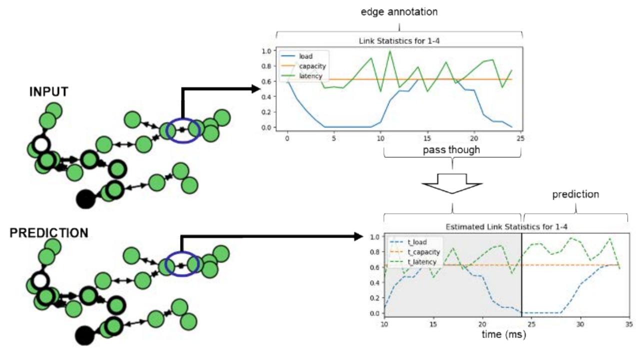

FIGURE 5. Input data and output predictions from Graph Neural Networks can be used to perform load and capacity balancing across communication links while minimizing end-to-end network latency.

the network links to predict the onset of congestion. Low priority traffic can be opportunistically re-routed onto under-utilized links to mitigate congestion before it happens.

The NC subsystem can be most easily described using the observe, orient, decide, act (OODA) loop framework (as shown in Fig. 4) for command and control described by John Boyd in [16]. The *observe* element of the loop is performed by the NC ingesting Open Systems Interconnection (OSI) layer 2 and 3 data describing the current state of Internet Protocol (IP) traffic flow and network topology. These observations are provided to the oracle, a predictive machine learning model within the inference engine. This model has been pre-trained under a wide variety of network conditions to become an expert model of network behavior. The *orient* step is completed using graph neural network (GNN) to generate predictions of latency and the load of each communication link in the network [17]. These predictions are provided to the route filter within the interference engine. The route filter performs the *decide* step, populating a congestion-aware route table which prioritizes low-utilization routes. Once the new routes have been dynamically adjusted, the router completes the OODA loop, *acting* to push low priority packets to seldom utilized routes in the network, leaving the quickest routes open for the highest priority traffic.

GNNs use neural networks to learn how relationships affect interactions, and in turn how those interactions affect the state of the nodes in the graph as shown in Fig. 5. Researchers have used these networks to solve n-body collision problems, networking problems to learn routing protocols [18], predict jitter and delay [19], optimize resource allocations [20], and perform distributed transmission scheduling.

IV. MODELING OVERVIEW

Operational modeling examines the architecture from the perspective of a system operator and other users who are concerned with accomplishing the tasks for which the system is intended. It deals with the environment in which the system operates, operational scenarios and interactions of the participants, the outcomes of employing the system in various ways, and measures operational performance and effectiveness [21]. Accordingly, operational modeling can be used to demonstrate the benefits of deploying such a CCS architecture within attributable platforms.

For context, an example use case for using the CCS architecture for interference mitigation is presented in Fig. 6 to show the importance of its utility, cognition, and subsystem interactions. Here, Drone-1 infiltrates enemy territory, and transmits surveillance data to Drone-2 and Drone-3. Drone-2 or Drone-3 acts as a communications relay and forwards data to the Operations Center (OC) for processing. Drone-2 and Drone-3 can communicate freely using 5G NR waveform when no interference is present. Red forces quickly detect the drones in the area of interest, and deploy an omni-directional, in-band, mature jammer to obfuscate communications between Drone-1 and its two intended receivers. The jammer then transmits on the same Receive (Rx) channel / Rx beam, thereby disrupting the communications and impairing the OC data collection efforts. The drones equipped with the CCS architecture by design can sense and characterize the interference and optimize the aperture parameters for the communications link while providing beam nulling in the direction of the jammer. In doing this, the drones can learn to implement the desired configuration for future deployed jammers as well. Additionally, with DSA aware technology, the SDRs can modify the given transmit and/or receive frequencies to avoid the spectrum congestion. Also, if other radios are available that operate at frequencies outside of those being jammed, the NC can select to route the data using those. The effect of these coordinated operations between subsystems within the CCS architecture enabled by machine learning is the successful receipt of data at the OC at increased rates during mission execution, even in the presence of jammers.

A. PERFORMANCE ANALYSIS METHODOLOGY

The following methodology was used to assess the jam resistance capabilities of the CCS architecture outfitted on the drones and its overall performance benefits.

1. 5G NR waveform fundamental link budgets for all communication paths available were performed. The

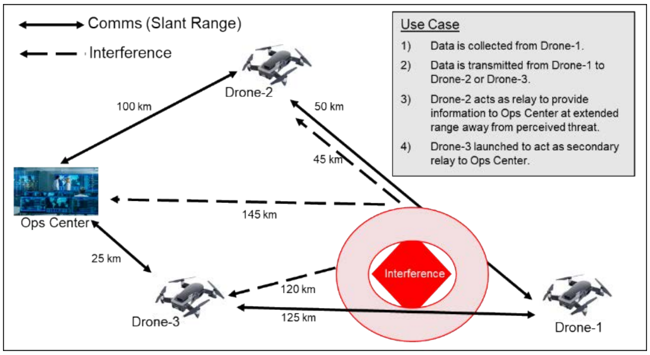

FIGURE 6. Notional operational scenario for mini-drone usage to extract data from behind enemy lines. Strong interference is present close-in range to Drone-1 thereby limiting communications reach-back.

analysis assumed a maximum operating frequency of 29.5 GHz, maximum available bandwidth of 850 MHz, and maximum channel bandwidth of 400 MHz as defined in the 5G NR specification [22].

2. Using the Friis equation for free space transmission, the jammer to signal (J/S) ratio was computed with the simplified equation derived below [23].

$$\frac{J}{S} = \left(\frac{P_J G_J}{P_t G_t}\right)\left(\frac{ds^2}{dj^2}\right) \tag{1}$$

Here, J is the jammer signal power at the intended receiver (dB), S is the transmitter signal power at the intended receiver (dB), P_j is the jammer output power (dBW), P_t is the transmitter output power (dBW), G_j is the jammer antenna gain (dBi), G_t is the transmitter antenna gain (dBi), d_j is the distance from the jammer to the receiver (m), and d_s is the distance from the transmitter to the receiver (m).

3. Using the jammer bandwidth, calculate the updated received C/N_0 due to the jammer which is a function of the received C/N_0, jammer bandwidth, and the J/S ratio. This equation computes the effect of the received jammer to signal power (J/C in equation below) on the received signal to noise ratio.

$$\frac{C}{N_o} = \frac{C}{N_{RF} + N_J} = \frac{C}{N_{RF} + (\frac{J}{C})(\frac{C}{B})} = \frac{\frac{C}{N_{RF}}}{\left(1 + (\frac{1}{B})(\frac{J}{C})(\frac{C}{N_{RF}})\right)} \tag{2}$$

where C is the total average received signal power, N_0 is the total noise power spectral density at the receiver, N_{RF} is the noise power spectral density due to the RF front end thermal noise, N_J is noise power spectral density due to jammer, and B is the jammer bandwidth.

4. The margin with the jammer can be computed, by taking the result in step 3 subtracted from the required C/N_0 obtained for the 5G NR waveform in use.

The methodology above was used to evaluate the physical layer communications analysis, the available margin with and without interference present, and repeated to understand the possible responses from the CCS architecture when exercising certain machine learning influenced decisions.

TABLE 2. Communications link budget analysis.

No.	Analysis Parameter (Unit)	Drone-1 to Drone-2	Drone-1 to Drone-3	Drone-2 to OC	Drone-3 to OC
1	EIRP (dBW)	20.0	20.0	20.0	20.0
2	Tx Frequency (GHz)	29.5	29.5	29.5	29.5
3	Range (km)	50.0	125.0	100.0	25.0
4	Free Space Path Loss (dB)	155.8	163.8	161.8	149.8
5	Atmospheric Loss (dB)	5.0	5.0	5.0	5.0
6	Pointing Loss (dB)	2.0	2.0	2.0	2.0
7	Total Propagation Loss (dB)	162.8	170.8	168.8	156.8
8	System G/T (dB/K)	15.0	15.0	15.0	15.0
9	Received C/N_0 (dB-Hz)	100.8	92.8	94.8	106.8
10	Information Bit Rate (dB-bits)	83.0	83.0	83.0	83.0
11	Required C/N_0 (dB-Hz)	89.0	89.0	89.0	89.0
12	Margin (dB)	11.8	3.8	5.8	17.8

B. PERFORMANCE ANALYSIS RESULTS

Considering the 29.5 GHz frequency band with 400 MHz carrier bandwidth for exercising the 5G NR waveform, and an EPA equivalent isotropic radiated power (EIRP) of 20 dBW (RF power of 1 mW and 50 dBi antenna gain), we can derive the physical layer analysis as computed in Table 2. Here, atmospheric loss was set at an arbitrary value of 5 dB to account for the loss affect expected at higher frequency bands. The results indicate that there is sufficient margin to close each link without interference present.

Next, consistent with steps 2 – 4 from the Performance Analysis Methodology section, the communications link margin results can be used as inputs into the jamming analysis. An omni-directional, in-band jammer with an EIRP of 30 dBW and instantaneous bandwidth of 150 MHz is introduced to interrupt the communication exchange between Drone-1 and Drone-2 and/or Drone-1 and Drone-3. The results are presented in Table 3; results demonstrate how mini-drones without an integrated CCS architecture would be vulnerable to deployed and fielded jammers. The jammer can disrupt the communication platform receivers which are using siloed apertures/antennas or standard radios such that the exchange of communications is halted between the drones that are close-in range which significantly impact the OC's data collection process.

The CCS architecture can apply cognition by using coordinated systems interactions among its subsystems to optimize the communication link. Fig. 7 depicts a decision flow chart for a CCS-enabled drone transmitting to another CCS-enabled drone.

TABLE 3. Jamming analysis without CCS architecture.

No.	Analysis Parameter (Unit)	Drone-1 to Drone-2	Drone-1 to Drone-3	Drone-2 to OC	Drone-3 to OC
1	Resulting Comms Margin (dB)	11.8	3.8	5.8	17.8
2	Distance between Tx and Rx Comms Nodes (km)	50.0	125.0	100.0	25.0
3	Distance between Jammer and Rx Nodes (km)	45.0	120.0	145.0	145.0
4	Jammer EIRP (dBW)	30.0	30.0	30.0	30.0
5	Jammer Propagation Loss (dB)	154.9	163.4	165.1	165.1
6	Jammer RIP (dBW)	-124.9	-133.4	-135.1	-135.1
7	Victim Receiver Gain in Direction of Jammer (dBi)	30.0	30.0	30.0	30.0
8	J_0 (dBW/Hz)	-176.7	-185.2	-186.8	-186.8
9	Victim Receiver Gain in Direction of Tx node (dBi)	50.0	50.0	50.0	50.0
10	Derived N_0 = kTs (dBW/Hz)	-193.6	-193.6	-193.6	-193.6
11	N_0+ J_0 (dBW/Hz)	-176.6	-184.6	-186.0	-186.0
12	C/ (N_0+ J_0) (dB-Hz)	83.8	83.8	87.2	99.2
13	Comms Margin with Jam (dB)	-5.3	-5.2	-1.9	10.2

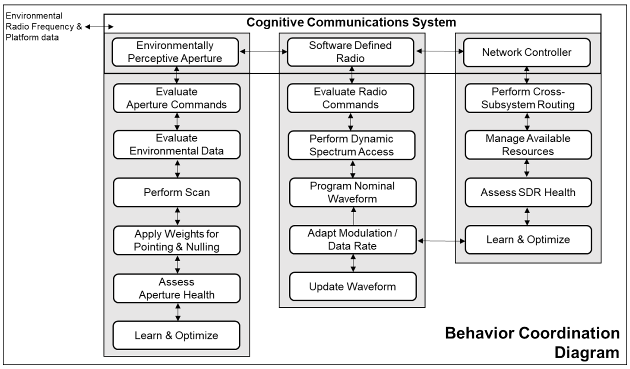

FIGURE 7. High-level coordinated systems operations with machine learning capable subsystems promotes effective communications.

Some techniques that the CCS can implement are define as nulling out of interference using adaptive beamforming methods, and if multiple interference sources exist, the segmenting of the EPA's EIRP based on the number of the gain required to close the link can be considered. Also, the CCS can exercise DSA by changing frequencies or transmit / receive channels to avoid spectrum congestion for in-band jammers. If multiple SDRs are available on the payload, the NC subsystem can seek an available communications link based on radio link resources and knowledge of the interference. Other techniques such as adjusting the data rate of the selected waveform to maximize range may be handy as well, or switching waveforms if alternatives are available for communications. To validate the significant offering of the CCS architecture, the jamming analysis was repeated where we assumed the drones were equipped with a CCS architecture. In this example, as the jammer is coming into position, the drones detect some of the degradation to communications and

TABLE 4. Jamming analysis with CCS architecture.

No.	Analysis Parameter (Unit)	Drone-1 to Drone-2	Drone-1 to Drone-3	Drone-2 to OC	Drone-3 to OC
1	Resulting Comms Margin (dB)	11.8	3.8	5.8	17.8
2	Distance between Tx and Rx Comms Nodes (km)	50.0	125.0	100.0	25.0
3	Distance between Jammer and Rx Nodes (km)	45.0	120.0	145.0	145.0
4	Jammer EIRP (dBW)	30.0	30.0	30.0	30.0
5	Jammer Propagation Loss (dB)	154.9	163.4	165.1	165.1
6	Jammer RIP (dBW)	-124.9	-133.4	-135.1	-135.1
7	Victim Receiver Gain in Direction of Jammer (dBi)	0.0	0.0	0.0	0.0
8	J_0 (dBW/Hz)	-206.7	-215.2	-216.8	-216.8
9	Victim Receiver Gain in Direction of Tx node (dBi)	50.0	50.0	50.0	50.0
10	Derived N_0 = kTs (dBW/Hz)	-193.6	-193.6	-193.6	-193.6
11	N_0+ J_0 (dBW/Hz)	-193.4	-193.6	-193.6	-193.6
12	C/ (N_0+ J_0) (dB-Hz)	100.6	92.8	94.7	106.8
13	Comms Margin with Jam (dB)	11.6	3.8	5.7	17.8

can recognize it as an enemy jammer. Using the knowledge gained on the jammer's position, a null can be applied in the direction of the jammer by using the EPA subsystem, thereby suppressing the victim receiver gain in the direction of the jammer. Table 4 provides updated results which yield positive communications margin for all communication path options.

Coupled with the fact that the CCA architecture meets or exceeds the platform and communication payload requirements, and the promising empirical results, the CCS architecture is an optimal selection for small attributable platforms deployed in highly contested environments.

V. CONCLUSION

A novel CCS architecture influenced by machine learning for attributable platforms which uses the 5G NR waveform to relay intelligence, surveillance, and reconnaissance to decision makers at the forefront of the battlefield was described. The architecture combines a highly capable EPA, a SDR, and resilient networking techniques. The CCS architecture and its hardware assets meet the SWAP requirements given for a medium size UAV and the communications payload. This paper described the system architecture and the machine learning application to designated functions within each subsystem, and the importance of systems orchestration to transfer information effectively between nodes, and across large-scale multi-hop networks. Operational modeling was performed to demonstrate the performance benefits of the CCS when presented with the challenges imposed by mature and readily available jammers. Performance results compared to existing commonplace architectures showed favorable results with the use of the CCS where an average improvement of 10 dB in communications margin was reported thereby maintaining the flow of information distribution from the data collection source to the processing center.

Future work will develop the selected machine learning algorithms as enablers for the CCS architecture. The CCS architecture will be integrated onto drones and staged in a testbed that applies a realistic operating environment to assess the immediate performance benefits for given use cases and will validate the interactions for collaborative systematic operations and decision making between the cognitive subsystems.

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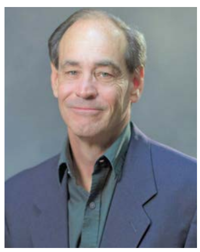

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