Artificial Intelligence based Electronic Warfare Systems: A Review

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Abstract

Electronic Warfare is one of the most important aspects of modern era Wars. Control of the spectrum, attack on adversary or obstruct the enemy assault using Electromagnetic spectrum are some of functions achieved as part of this warfare. Upcoming trends in AI indicate that, evolving EW technology will have a revolutionizing influence on Armed Forces. AI based algorithms can be very productive in various fields of EW viz. signal processing for recognition and classification of targets, revelation of Jammers and its characteristics for evolving suitable anti-jamming algorithms as well as satellite signal monitoring and interception. Autonomous operation of EW systems can also be realized using AI based approach. This paper gives an insight on different aspects of EW, the usage of AI in EW systems and different techniques that have been incorporated in conventional and Satellite based systems.

Keywords: *Electronic Warfare, Satellite Communication, Artificial Intelligence, Learning*

I. Introduction

Current-era Armed Forces rely on various developing technologies for effective usages of EW spectrum to get the edge over adversaries. EW system helps in monitoring and securing the RF spectrum to gather the intelligence and nullify the enemy targets electronically. In spite of having vast improvement in war fighting capability because of deployment of EW systems, Armed forces continue to face hurdles in optimal resources management and effective decision support. AI based system are expected to narrow the gap between expected war-fighting capability and existing skills.

AI based system for EW applications are being considered for tactical deployment. Essential reasons for AI being used in EW applications are management and analysis of huge data, decision support, situational awareness, visualization of conflict zones/threats, and counter measures based on approximate responses. This paper describes various traits of EW, it's building blocks, and relevant technologies of current EW systems, as well as AI usage for decision making in war zones.

II. Electronic Warfare

EW is basically use of RF spectrum to intercept, identify, analyse, monitor and deceive/neutralize adversary's electronic systems while protecting own assets upon such attacks. These technologies are mainly targeted for communication systems and RADARs which are extensively being used by Armed Forces. Three major areas come under EW viz. Electronic Support (ES), Attack (EA) and Protection (EP). ES techniques are targeted for monitoring, intercepting, and analysing possible adversaries. Similarly, EA based techniques are mainly focussed on Deception/Jamming to protect against DoS attack for EW spectrum within our territory whereas EP techniques are emphasized on protecting own assets while using RF spectrum whereas. Overall EW system architecture which includes functions such as ES, EA & EP is shown in Fig 1.

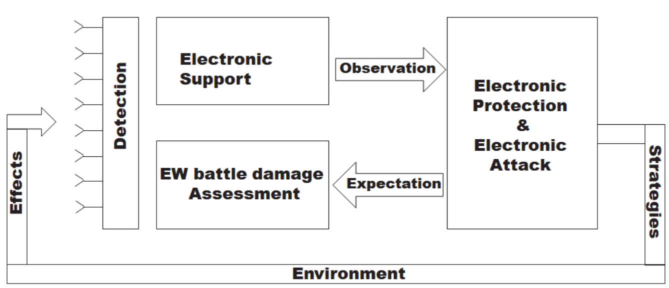

Figure 1: Functions of EW in System Architecture [1]

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A. Problems faced by existing EW Systems

1. Typically, systems operate over BW of at least 2-3 octaves. It may perform RADAR, EW Radiometric and communication functions necessary for survival of a platform at assigned frequency. Many EW systems have issues such as multiband antenna, multiplexors, LNAs, transmitters, which are required to operate over targeted broad BW (typically multi-band).
2. Problems related to a system that performs a wide range of EW functions when threat vary dynamically and prime power available is limited.
3. The requirement may arise due to exercise of Jammers in spatial and frequency domain simultaneously.
4. Modern day SDRs & cognitive RADARs employ dynamism which poses a challenge for characterization.
5. Complex target parameter estimation such as classification, intra-pulse analysis, decoding, processing of real-time data streams etc.
6. In communication systems, Several challenges are being faced by designers in satellite communication area although it provides better coverage and quality of communication. Typically, LEO satellites have bare minimum on-board resources and travel fast because of low altitude bring intense dynamics to network access which demand suitable handoff management between satellites.
7. Various other issues of EW systems based on satellite communication also need to be focussed such as Multi-Input-Multi-Output (MIMO) system [2], Network of Remote Things [3], Inter-Satellite Communication [4], Quality of Service [5] and Physical Space Security [6] etc.

B. Role of AI in EW Systems

EW applications fall in two major types of groups/categories viz. strategic level and tactical for various operations of War. The strategic level application of AI consists of functions such as order of wars/battles, assignment to Armed Forces, War Strategy and decisions, scale and escalation of War, intelligence gathering, information interpretation, scope and nature of battle, deployment of Armed Forces and Assets. The Tactical level applications of AI consists of aspects related to short-term objectives, immediate planning, removing immediate uncertainties and preparation for War etc.

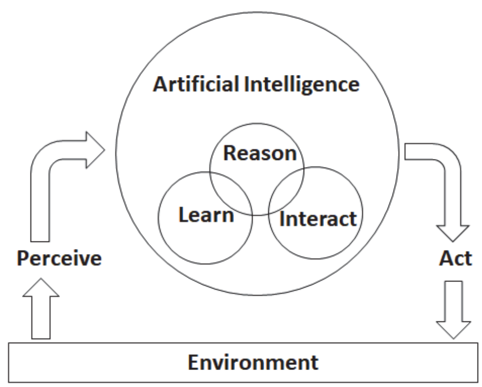

Figure 2: AI perspective EW Systems [1]

Usage of AI in EW systems is responsible for paradigm shift in utilization and protection of EM spectrum. AI based approach is main driving force to make EW systems more effective and autonomous [7]. Because of huge requirement to automate the EW systems, AI techniques are being explored to get value addition along with basic EW capabilities such as assistance in decision making, analysis of big data, simultaneous processing and identification of multiple targets and graphical simulations for war-games etc. Also, AI is useful in Threat analysis, intelligence gathering and logistic support. AI perspective of EW system is shown in Fig 2. EW system perceives threat using AI to learn, reason and interact with EM Environment and formulate the counter measures.

Various aspects of EW systems which includes Pre-Mission, ES, EA & EP as well as Electronic Battle Management and Data Management are shown in Fig. 3. The add-on AI functions such as mission planning, resource allocation, decision assistance, characterization, classification, data fusion, intent recognition, scheduling and coordination play complementary role in enhancing the overall capabilities of EW systems

C. AI Model Selection

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AI consist of various sub-fields; each in-turn may have multiple approaches. The learning in AI technique can be supervised, unsupervised or reinforcement based. It can be deeper or shallow learning. Typically, with common notion it is presumed that deep learning is superior to shallow learning, which is actually the case except computer vision problem. The DL techniques demand higher computational resources and huge dataset which are not always present. Moreover, supervised learning is a better approach when complete labelled dataset is present. However, this may not be possible always since data can be costly, challenging, unavailable or even may be extremely difficult to get. Different work functions of AI useful for EW capabilities are listed in Table 1.

Table 1: AI Functions in EW world [1]

Sl. No.	AI Term	EW term
1	Situational Assessment	Electronic Support (ES)
2	Decision Making	Electronic Protection and Attack (ES & EP) Electronic Battle Management (EBM)
3	Executive Monitoring	Electronic Battle Damage Assessment (EBDA) Effects analysis
4	Learning	EW Reprogramming (Data & Software)

Similarly, it is easy for unsupervised learning/RL based algorithm to find hidden pattern in non-labelled data. Hence, unsupervised learning is a good technique to extract the information from given dataset, whereas reinforced learning is better for decision making jobs. Therefore, the AI algorithm should be chosen based on characteristics of problem, amount and quality of data, computational resources and time limitations etc.

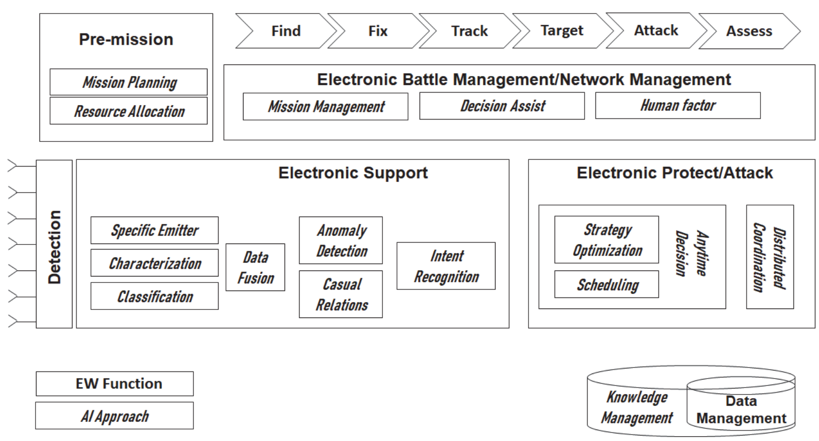

Figure 3: AI perspective EW Systems [1]

AI system needs to be trained on datasets for effective outputs. Typically, Artificial Neural Network (ANN) based systems require huge data to train the algorithm sothat effective weights are adjusted to meet the requirements. Similarly, self-learning algorithms keep adapting to the new environment and adjust weights continuously.

D. AI based EW system at Strategic level

1. Surveillance, Intelligence, and Reconnaissance (ISR) capability is extremely important to get multi-domain situational awareness with available data. AI can analyse huge data in real time to give better perspective for dynamic War situation. Additionally, AI can assist the operator in making the decision to analyse, identify and attack the target with best resource management.

2. AI is useful in formulating War strategies, battlefield simulation and train Armed Forces to War-games, and improve navigation system for effective target acquisition, tracking, identification and validation.
3. AI steered exploration, mapping and systematic hacking of enemy computer network to collect information for War tactics.

E. AI based EW system at Tactical level

1. AI in Unmanned Air/Underwater Vehicles: AI enhanced navigation system helps to find the target path for UAV, Underwater Unmanned Vehicle in enemy territory. AI powered Vehicles/Drones may carryout advanced war tactics and adapt to enemy war strategies to exploit on field opportunities.
2. AI based systems for collection, interpretation and analysis: Various information as a part of military war is gathered from different systems such as electronics intelligence, signal intelligence, and communication intelligence etc. Data collected from these systems need careful scrutiny and analysis to conclude the relevant interpretations.

III. Review of AI applications

A) AI for EW perspective usages

Different AI techniques are being used in EW systems such as Convolutional Neural Network (CNN), Deep Learning and Neuro-computing etc., which helps in acquisition of surrounding acquaintance.

a. AI is very much useful in automatic detection and classification of modulation for RADAR EW, Communication EW and Data Processing & Analysis. AI algorithms such as SVM and Bayesian are discussed in [8] to extract various attributes of monitored signal using Time and Frequency analysis, DFT and Autocorrelation. Anti-Jamming method against Intelligent Jamming using Reinforcement Learning based AI technique has been discussed in [9].
b. A scheme based on Deep Learning has been proposed for selection of antenna for Cognitive RADAR systems [10]. Identification of Jammers and determination of attack characteristics are presented in [11]. The Jammer being used for software defined radio is identified using Deep CNN and Deep RNN techniques.
c. A novel AI based algorithm using probability moment and approximate Entropy is being used for RADAR signal classification [12].
d. Typically, ESM receivers need to process huge amount of real time data, hence a compressive sensing (CS) technique can be employed to reduce computational cost. Various algorithms such as Artificial Neural Network (ANN), Decision Tree (DT), Naïve Bayes (NB) [13], are used for classification of 5 different antenna scan types. Compressive Sensing based ESM receivers need a handful of compressively obtained data to detect and locate the targets.
e. A ESM Receiver system has been discussed in [13] to evaluate Doppler angels of enemy targets whose details are not known using Sparse Bayesian Learning (SBL) algorithm. A novel approach to carry out Cyber Electronic Warfare (CEW) tasks for target identification using Deep Reinforced Learning has been discussed in [14]. The approach briefly discusses about mitigation techniques for spatial sparsity, obstructive, partly obstructive surroundings and continuous actions required for cognitive/self-learning EW systems.
f. Channel Modelling, and remote sensing application make use of Support Vector Regression.
g. Channel modelling, Satellite Telemetry, Network Traffic Prediction, Interference Management and Remote Sensing make use of Decision Tree based AI technique.
h. Remote Sensing, Channel modelling, Inter-Satellite Hand-off Management, Unknown Signal Detection and Identification using CNN.
i. Satellite Telemetry, Anti-Jamming, Satellite Hand-off Management use RNN based AI algorithm.
j. Auto-Encoder based AI Technique has been used for Signal Interference Management.
k. Anti-Jamming, Satellite Beam Hopping, Interference Management and Energy Management may use Reinforcement Learning.

B) AI for Satellite Communication perspective usages

AI is being used extensively for satellite-based systems for various functions such as Beam Hopping, Anti-Jamming, Network Traffic Prediction, Channel Modelling and Carrier Signal Detection.

i. Beam Hopping*:* The resources at satellite are scarce and expensive, hence need optimal resource usage and time sharing. Traditional satellites system has multi beam configuration and there may be mismatch in resources available and demand at any given time, since there may be uniform distribution of resources across each beam. So, high demand spot beam may have higher waiting period to complete the communication. Similarly, for better utilization of multi-beam communication satellite system, flexible resource allocation based on demand needs to be employed for better service to larger coverage area. It has been observed that, Beam Hopping is an effective technique to cater non-uniform and volatile traffic request at any given time [15,16]. In this technique satellite highlights (activates) few narrow beams within a broad regional beam based on traffic demand. The narrow spot beams are selected in time variant manner to cater the traffic requirements. Hence the critical tasks in such system are to select the narrow beam dynamically and amount of time till the beam remains activated.

A generic AI based approach on Genetic Algorithm has been proposed by Angeletti et al [17] for selection of beam in BH system. It has also shown that BH scheme reduce the number of Transponder transmission amplifiers for Terabits/sec speed satellites. An iterative technique with combination of BH scheme and spectrum assignment to optimally use offered network capability under the traffic demand and power limitations [18].

Hu et al [19] has proposed DRL based approach to optimally use system throughput with different transmission delay in a multi-beam satellite system using on Markov Decision Process (MDP) model. This approach makes use of long-term accumulation reward optimization and has shown the reduction in transmission delay by 52.2%. Similarly, it has increased the system throughput by 11.4% compared to conventional algorithms. A novel approach which is combination of optimization and end-to-end learning for best selection in Beam Hopping system using fully connected Neural Network has been employed [51]. The self-learning pre-trained algorithm has been used to estimate feature vectors to select useful data in a large search space.

ii. Anti-Jamming: Satellites utilized in military communication system need to be reliable and secure. Hence, anti-jamming capabilities are necessary. Various types of attacks are possible which may limit or disrupt the communication entirely. Considering this, frequency hopping, and spread spectrum technique are frequently being used in satellite based tactical communication systems [20,21]. Bae et al [23] used Frequency Hopped Frequency Division Multiple Access using hop-dehop transponder. Conventional anti-jamming techniques cannot counter intelligent jamming techniques based on self-correcting attack methodology which monitor the enemy signals and continue learning. In this context, [24,25] proposed self-adjusting, Smart Jammer to vary the jamming power and channel number. Lec et al [26] used a long term-short term Memory Network based on Reinforced Neural Network (RNN) to learn the time domain aspects of the signal. A reduction in overall synchronization time in FH-FDMA situation has been demonstrated in [26].

A novel approach using RL in mobile communication terminals can work seamlessly without need to know about jamming or model for radio channel in the dynamically changing scenario [27]. A learning technique to counter smart Jamming using space based anti-jamming approach for Internet of Satellites (IoS) application has been demonstrated by Han et al[28]. He has also combined Reinforced Learning and Game Theory algorithm to demonstrate the usage of Deep Learning to deal with huge decision space generated by virtue of dynamics of IoS as well as interplay between satellites and Intelligent Jamming surrounding.

iii. Network Traffic Prediction: Predicting traffic in a network is a pre-emptive approach to ensure reliable and good quality communication. Various aspects of satellite communication such as Traffic Congestion Control, Dynamic Channel Allocation and Management, Dynamic Routing Control, Network Planning and Security can be managed effectively using such predictions [29]. Many of scholars have predicted network traffic for satellite and terrestrial networks using various technique such as Auto-Regressive Moving Average (ARMA) [30]. Neural Network based approach has been proposed by Katris and Daskalaki [31], whereas a combination on Neural Network with differential evolution has been used by Pan et al [32] for internet traffic prediction. A least square SVM technique using classification and Regression analysis has been used for prediction [33]. Similarly, Liu and Li [34] have used principle component analysis to get smaller set of input dimensions using Regression Neural Network and achieve better accuracy in prediction with reduced training period. Distributed routing for LEO satellites has been discussed by Na et al [35] to predict the traffic in the network. Another researcher [36] used Extreme Machine Learning to predict the traffic congestion before routing.

iv. Channel Modelling: It is a mathematical illustration of communication channel behaviour used for wireless signal propagation, which is usually the impulse response represented in Time/Frequency domain. Typically, a channel has various impediments such as noise, interference and path loss along with shadowing etc.

True real channel models are essential to evaluate and understand the performance of communication system considering various vulnerabilities for reliable operation. These models may be useful to predict the signal propagation which would be useful in pre-deployment phase and to best utilize the coverage and channel capacity. A stochastic model [37] has been used for wireless communication to estimate channel parameters.

Researchers have used Machine Learning approaches such as SVM [38,39], Neural network [40] & Decision Tree [41] to predict path-loss for given media.

Ates et al [42] used Deep CNN algorithm to estimate channel parameters and variance in shadowing to get the path loss exponent. Thrane et al [43] used Deep Learning model on satellite photographs along with other parameters to predict Reference Signal Received Power (RSRP) at specific locations. Additionally, Ahmadien et al [44] proposed Deep Learning approach to predict the path loss using satellites' 2D images having generalized data.

v. Carrier Signal Detection: Typically, in wireless communication signal is processed by means of modulation, encoding and encryption etc. to optimally use the channel BW. Each of the above-mentioned function need to be performed over signal to extract the plain message. Algorithm to detect carrier signal based on Threshold values which require human mediation has been proposed by [45]. Another researcher Kim et al [47] discussed the use of slope tracing-based approach to investigate signal based on various parameters such as amplitude, signal slope, deflection width and distance between consecutive deflections.

Morozov and Ovchinnikov [48] made use of fully connected Neural Network for detection of carrier signal. Similarly Yuan el al[49] used Deep Learning algorithm to differentiate signal blind detection in wideband. A fully Convolutional Network based model has been proposed by Huang et al[50] to identify the signal in broadband power spectrum.

IV. CONCLUSION

Current era Armed Forces need systems that use highly robust and adaptable EW systems with feedback to adjust rapidly against EM surrounding because of innovation in digital technology. EW systems based on AI are very much important considering above scenario. Automation of EW systems have become possibility with use of AI which may improve situational awareness and make decision making more trustworthy. Considering this, an AI based EW system may become more effective in recognizing the enemy radar & communication emitters so as to investigate the lethality of the threat and use suitable counter strategy to destroy the hostile EW threat. The usage of AI has shown huge improvements in various EW and satellite communication systems such as RADAR operation in multi threat scenario, Threat classification, ESM, Anti-Jamming, and Radio design etc.

The paper gives a brief assessment of EW's fundamental aspects, problems faced by current systems and the importance of AI techniques in modern EW including satellite systems. Future work in EW should focus on application of AI to accomplish more efficient, secure, trustworthy, and better-quality communication systems.

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