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Simulation of Cognitive Electronic Warfare System With Sine and Square Waves

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ABSTRACT

Today's Electronic Warfare (EW) receivers need advanced technology to achieve real-time surveillance operations. Dynamic and intelligent systems are required for UAVs and other airborne applications. The airborne Electronic Warfare systems must be knowledge-based systems, learning from the threat scenario with highly integrated capabilities to detect, react, and adapt to radar threats in real-time. Artificial intelligence is a machine-dependent process, by adapting certain rules and logic supported by human intelligence, AI can be used for cognitive processing. Cognitive signal processing is required for making the system autonomous and dynamic in nature. Military action on radar signatures requires a set of commands to be executed dynamically with the help of the proposed EW system. It is proposed to design and develop a cognitive EW architecture and simulation of machine learning that combines neural network architecture with the help of sine and square waves as input. This paper presents the Cognitive signal processing for EW systems with Neural Network, Recurrent Neural Network (RNN), Machine learning (ML), and Deep learning (DL) techniques with their simulation with sine and square waves.

Keywords: Cognitive EW; Deep learning; Electronic support measure; Machine learning; Neural networks

NOMENCLATURE

AI	:	Artificial intelligence
DL	:	Deep learning
ECM	:	Electronic countermeasure
ESM	:	Electronic support measure
EW	:	Electronic warfare
ML	:	Machine learning
NN	:	Neural networks
RNN	:	Recurrent neural network

1. INTRODUCTION

Radar signature recognition is very important in future LPI, MIMO, and cognitive radars to handle the EM spectrum. Ultra-wideband (UWB), Active Electrically Scanned Array (AESA) radar, and Low Probability of Intercept (LPI) radar technologies are the current trends in modern radar systems[10]. Because these systems are digital and programmable, they can use different frequencies, signal characteristics, and waveforms to avoid jamming. Current EW digital receiver systems are modular with federated architecture, in wide or narrow band configurations, with an operating frequency range of 0.5 to 40 GHz, to capture the electromagnetic scenario in real-time with a high probability of intercept[1]. Current electronic warfare systems use statistical collectors to determine the likelihood of capturing electromagnetic radar signatures. The design, development, integration, and testing of EW frameworks involve an enormous amount of human effort, and these frameworks could not learn and store radar signatures over a long period of time[2]. When the radar is transmitting on one frequency and the EW system jams that frequency. The radar then changes frequency, and the EW jammer jams once more. If radar functions change rapidly, we need EW systems that can respond in similar time frames to protect the aircraft. The radar is hopping in frequency, and then the EW jammer dynamically jams all the frequencies. If the radar is changed by other parameters, cognitive signal processing is required to change the parameters as well[3]. For learning electromagnetic radar scenarios, long-term memory and fast decision-making requires an expert system using cognitive signal processing[4]. Systems like UAV's are being used with and without licence band may require this kind of system with Cognitive radio-based detection of signatures[18].

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2. LITERATURE REVIEW

Cognitive signal processing is required for making the system autonomous and dynamic in nature. When common sense is integrated over a long period of time, some concepts are created in human life. These concepts are integrated over years as the characteristics of humans are formed. When these characteristics are integrated over a long period of time, an experience is formed in the life of a human. Artificial intelligence is a machine-dependent process with certain rules and logic that needs to be supported by human intelligence to improve cognitive processing[5]. Figure 1 depicts the generic artificial intelligence processing framework proposed for EW systems. The proposed system is designed to receive signals in the range of 0.5 to 40 GHz. The framework of the AI is applied to all the signals to classify the signals of interest in the proposed cognitive Electronic Warfare is presented in Fig. 1.

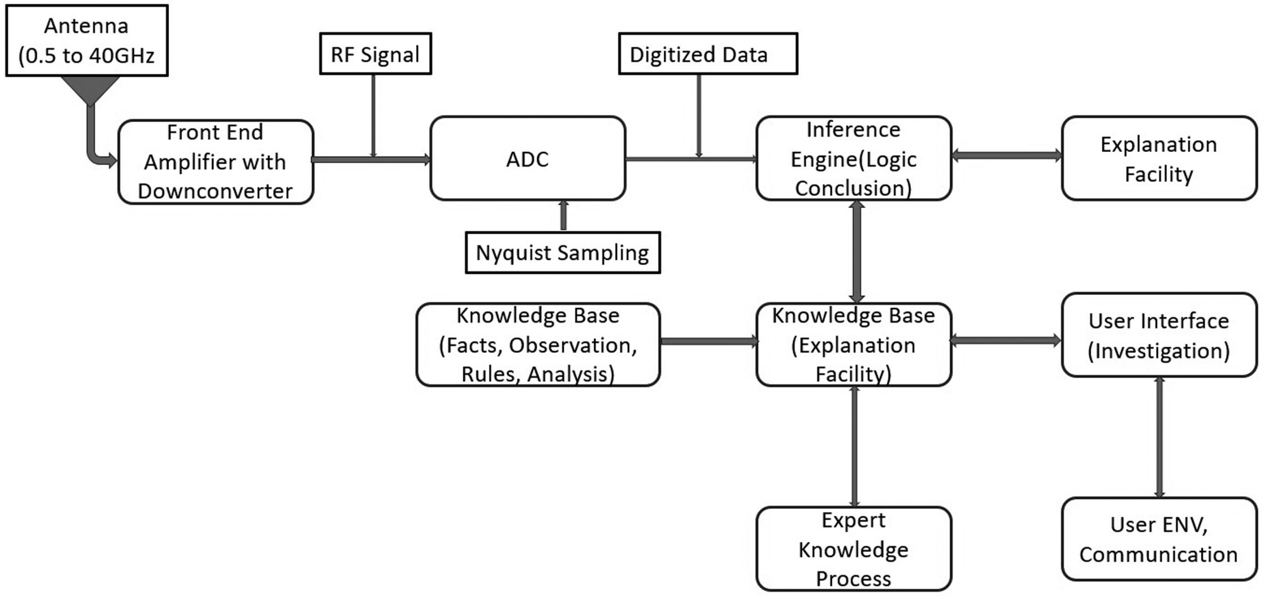

Figure 1. Artificial Intelligence processing framework for EW systems.

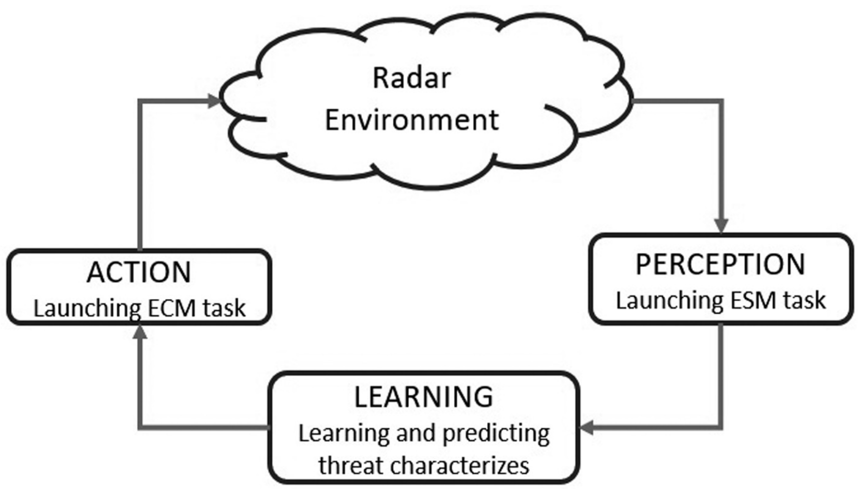

Figure 2. Cognitively closed loop cycle in EW framework.

As per the concepts of cognitive signal processing techniques, the skills are the core skills utilized to think, read, learn, remember, reason, and pay attention to the specific area where they are implemented[6]. The same is proposed and implemented as part of Electronic Warfare with Cognitive skills for work together to take incoming information in the form of all signals of interest and non-interest and convert them into the knowledge base for the application of implementation, but the integration of artificial intelligence and human intelligence is an essential requirement. This can be done in three important ways as mentioned here and the proposed cognitive EW system differs from adaptive systems.

- The receiver continuously learns about the environment through interactions with it and is constantly updated with relevant information about the environment
- The cognitive-based systems can sense the RF environment and adapt to it, and can rapidly respond to dynamic changes in radar parameters, real-time decision-making, and associated tactical execution
- The sparse radar signal acquisition with minimum samples by projecting to the union of subspaces and recovery is an optimum acquisition system matching to physical signal that can be designed.

The entire EW system is a closed, dynamic feedback loop that includes the jammer, radar environment, and ESM receiver. Figure 2 depicts a cognitively closed loop cycle in the EW framework. The ESM and jammer intelligently adjust their illumination of the environment, considering practical matters in the time, frequency, and angular domains, and jamming the radar in an effective and robust[14]. The entire EW system, including the jammer, radar environment, and ESM receiver, is a dynamic closed feedback loop. While designing the jammer, care must be taken for dynamic closed-loop feedback[15].

Cognitive intelligence is very much required for developing autonomous and dynamic systems, as the development of cognitive EW systems needs the design of machine learning and deep learning algorithms will be adapted as per the closed loop cognitive cycle. A cognitive machine is a brain created by proper learning machines that will help humanity perform many critical tasks that human beings cannot execute[13].

This paper presents the cognitive signal processing-based analysis of the EW signals with the help of neural networks (NN), Recurrent Neural Networks (RNN), Machine Learning (ML), and deep learning techniques. The same is presented in Section 2. The design of the cognitive EW system is presented with the proposed algorithm, along with the configuration of AI-based EW system functional blocks, and the simulation results of the machine learning algorithm with learned and hidden square and sine waves are presented in Section 3.

3. COGNITIVE SIGNAL PROCESSING

The EW system will change into an intelligence-based system for learning various threats and taking appropriate action with cognitive-based signal processing. Cognitive signal processing can address the study of Electromagnetic (EM) scenarios, controlling the RF front end to operate scenario-specific operations and suppress noise with interactive speech and situation display. The ability to recover frequency information from low-rate sampling could be the key to effective spectrum sensing in cognitive processing. Cognitive processing rapidly identifies signals in the EM spectrum over a very wide bandwidth and also makes reliable decisions in noise-uncertain environments[7]. The depicted block diagram as Fig. 3 defines the EW cognitive signal processing framework.

The cognitive cycle begins when radar signals from the environment are fed into two functional blocks: the radar-scenario analyzer and the Bayesian radar tracker[9]. Based on information about the environment provided by the radar-scenario analyzer, the tracker makes real-time decisions about the possible presence of radars. In turn, the transmitter illuminates the environment based on potential radar decisions that are fed back to it by the receiver. After that, the cycle is repeated indefinitely. Because the radar receiver and jammer are usually co-located, implementing the feedback mechanism, which is a requirement of a cognitive system, is simple. Although target detection is not explicitly depicted in the cognitive cycle, it is a component of the Bayesian radar tracker, which performs detection through tracking. The integration of artificial intelligence with human intelligence is an essential requirement to make the Cognitive system knowledgeable in separating the signals of interest.

The EW requires a powerful, integrated framework that supports “sense, learn, and adapt” capabilities, also known as cognitive RF, in order to limit the enemy’s use of the electromagnetic spectrum, secure it for friendly forces, and provide situational awareness of the electronic battle space. The cognitive RF “sense” phase automates pattern detection functions for signal classification from an emitter’s semantic description[11]. During the “learn” phase, the residual signals are scrutinised for discernible patterns. When the unknown is discovered, it is automatically encoded and becomes a significant addition to the threat’s knowledge, resulting in a newly learned capability. The end result is an improved knowledge store containing descriptions of all previously known and recently learned emitters. During the “adapt” phase, the newly learned capability is used to detect the previously unknown source, and the system responds appropriately to the signal’s source[12].

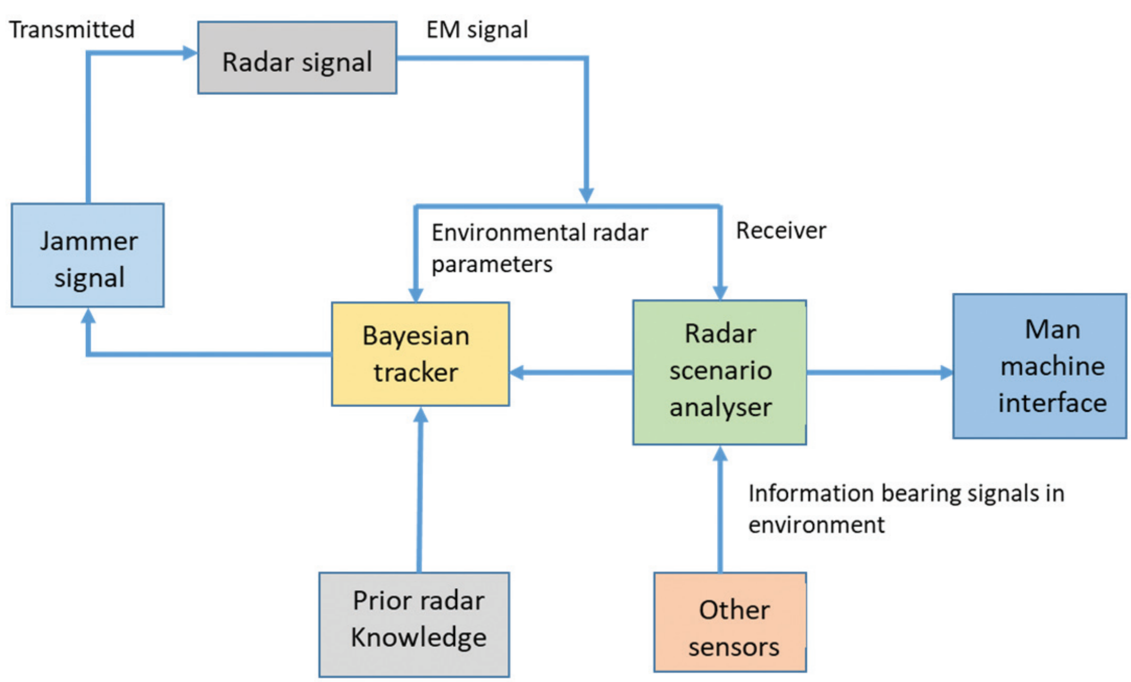

Figure 3. Cognitive signal processing framework.

Sub-Nyquist sampling plays an important role in future cognitive systems because the algorithms used in cognitive processing are dependent on scenario data. The scenario data for radar signature identification and jamming can be exercised with the cognitive signal processing cycle. In EW, from the antenna to the low-rate sampling stage, compressed sensing acquisition is required to be used for matching with radar signals. The cognitive signal processing takes low-rate compressed sensing samples and processes them with a Bayesian tracker to optimize the identification for displaying and cueing to Jammer. The requirements of Neural Networks (NN), Recurrent Neural Networks (RNN), Machine Learning (ML), and deep learning techniques are presented here to adapt them for the cognitive signal processing of EW applications.

3.1 Neural Network

A neural network is a network or circuit of neurons or, more recently, a synthetic neural network made up of artificial neurons or nodes. As a result, a neural network can be either a biological neural network made up of real biological neurons or an artificial neural network designed to solve problems involving Artificial Intelligence (AI). Weights are linked to an artificial neuron's input. A connection is indicated by a positive weight, while a broken link is indicated by a negative value. All inputs are modified by the weights and summed to produce the weighted average of the signal. This activity is referred to as a "linear combination" of the input signal with weights. Finally, an activation function like ReLU or sigmoid controls the weighted amplitude against a threshold for providing the output. For example, an acceptable output range is usually between 0 and 1, but it could also be between 1 and 1. Cognitive senses of attention, memory, and dynamism depend on the structure of the neural network. Dynamism is related to the exercise of the structure and is related to the rate of operation of the neural network, which is approximately 50 MHz. The general and standard artificial neuron configuration is given in Fig. 4.

Each node in the neural network has its own domain of knowledge, which includes rules that it was programmed with as well as rules that it has learned on its own. The key to neural network efficacy is that they are extremely adaptive and learn very quickly. Each node considers the significance of the input it receives from the nodes preceding it. The inputs that contribute the most to the correct output receive the most weight. Figure 5 depicts a flow chart of a neural network that describes the neural network's function which will be applied in the proposed system. The radar signal samples are multiplied or convolved with coefficients and summed. The sum is compared against the threshold. The sum above the threshold is the output value.

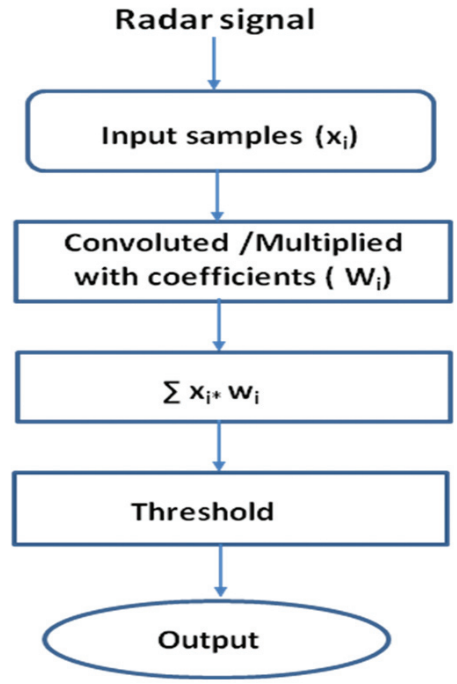

Figure 5. Flowchart of artificial neuron.

3.2 Recurrent Neural Network

The Recurrent Neural Network (RNN) is based on the principle of saving a layer's output and feeding it back to the input to aid in the prediction of the layer's outcome with long short-term memory. The first layer is constructed in the same manner as a feed-forward neural network, using the product of weights and features. Each neuron remembers some information from the previous time step as the recurrent neural network process begins one time step at a time. When performing computations, each neuron acts like a memory cell. We must allow the neural network to work on frontal propagation and remember what information it requires for later use during this process. If the prediction is incorrect, we use the learning rate or error correction to make small changes so that backpropagation can gradually work towards making the correct prediction. The proposed technique follows the standard recurrent neural network with a multilayer configuration.

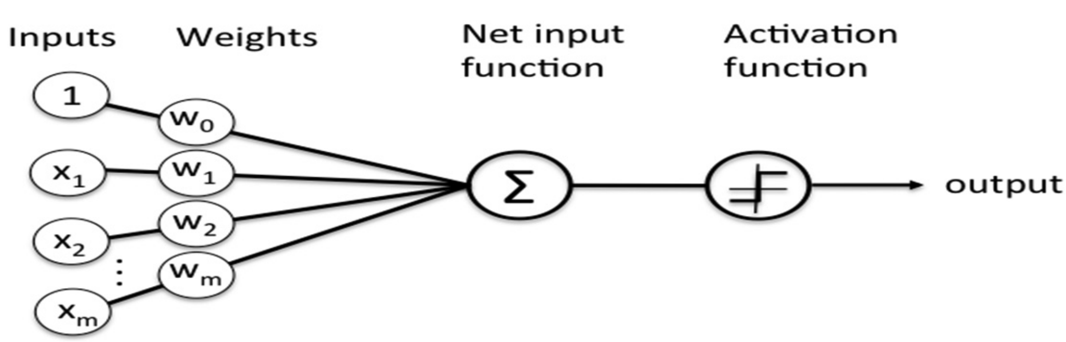

Figure 4. Standard of artificial neuron.

3.3 Machine learning

Machine Learning (ML) is an application of Artificial Intelligence (AI) that gives various frameworks the capacity to automatically learn from experience and improve without being explicitly programmed. Experience learning is inductive learning and is used to assess ML performance. The ML system processes the collection of framework features that have been quantitatively estimated from the received information. ML will be useful in the electronic warfare framework to monitor all the radars to be dynamically jammed and displayed, which enables automatic radar tracking with voice interaction. We must design an ML algorithm to perform a specific task, and it focuses on the development of software that can access information and utilise it to learn. Machine learning performs this by defining tasks, taking execution measures, and using the experience learned from the system's received data.

Most ML calculations are of two types: administered learning and unaided learning. ML calculations perform best within a reasonable capacity, and they depend upon the true complexity of the task and the measure of training data. By changing the limit of the model, the underfitting and overfitting of training information can be controlled. The model's over- and underfitting can be limited by modifying its ability by selecting its speculation. The challenge in machine learning is the generalization of training information and the low error rate of test information. We use optimization methods to reduce the error rate. The training and test information is created with an identically independent probability distribution function over informational indices, a process called the information-producing process. Learned portrayals frequently result in far superior execution than hand-designed representations. This feature allows AI frameworks to quickly adapt to new tasks with minimal human intervention. At optimal capacity, the test error asymptotes to the Bayes error. Due to the training algorithm's ability to remember specific instances of the preparation set, the training error can fall below the Bayes error.

3.4 Deep Learning

Deep Learning (DL) is a novel machine learning method that is based on feature learning and hierarchical architectures. The ability of traditional machine learning algorithms is limited by factors like Big data size, handling of complex problems such as image classification, natural language processing, computer vision, speech recognition, and lower accuracy. When the data size is large, the problems are complex, and the accuracy is high with large amounts of information, DL outperforms other techniques. DL classifiers are trained through feature learning rather than task-specific algorithms. DL is implemented using artificial neural networks with multiple layers between the input and output layers. A deep neural network is defined as having more than one layer. Deep learning algorithms are mainly of two types: convolutional neural networks and Bayesian neural networks.

The goal of deep learning is to exploit pattern analysis or classification to compute hierarchical features or representations of observational data. DL calculations have a longer learning time compared with the traditional feature extraction method, deep learning could extract the required features from the original data set, and its execution time is lower. Deep learning focuses on the model structure, which is composed of multiple hidden layers built by non-linear function composition. Multi-layer perception with many hidden layers is used to extract internal representation and build the feature matrix from rich sensory inputs[8].

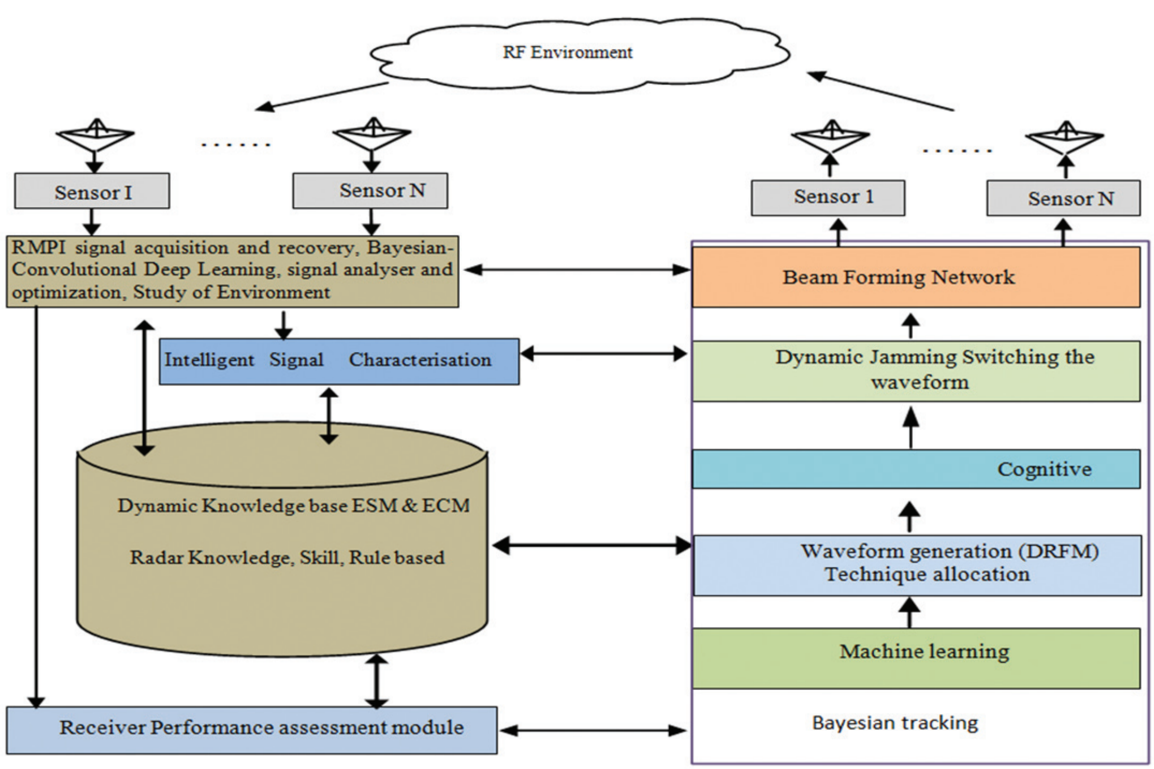

Figure 6. Configuration of AI-based EW system functional blocks.

4. DESIGN OF COGNITIVE EW SYSTEM

The human cognitive senses, like creativity, punctuality, and specialized human skills, are to be explored in depth. The standard neural network training via optimization is equivalent to maximum likelihood estimation for the weights and biases. The configuration of the EW system's different functional blocks is shown in Fig. 6. The compressed sensing-based data acquisition system produces a minimum number of samples of the electromagnetic radar signal and recovers them through a convex recovery algorithm. The recovered signal is fed into a deep-learning Bayesian convolution network to obtain a high-resolution radar signal. Signal analysis and optimization are carried out based on the obtained radar signal study for the radar scenario. The optimized radar signal is intelligently characterised and compared with the ESM database. Finally, the receiver performance module identifies all the radars in the scenario and cues the specified radar information for jamming.

The ECM system collects the information to be jammed and tracks the radar signal through the Bayesian tracker. When the ECM system receives the multi-radar signal, all the radars are tracked in real-time through the Bayesian tracker. The machine learning algorithm learns which radars are jammed and cues the technique allocation and waveform generation modules[19,20]. The cognitive decision module, which employs fuzzy logic, dynamically switches all of the radar waveforms with the assigned technique and can change the radar's various modes, angles, and frequencies, as well as synchronously jam all of the radars in real-time via a beam-forming network and active array. If jammed, the radar loses track, and this will be inferred from the receiver. The EW system is software intensive and performs multi-dimensional signal processing in real-time at approximately 100ms17. We have developed own software to simulate the proposed EW technique using Python script and simulated the sine and square waves based cognitive radio environment.

```python
from keras.layers import Input
from keras.models import Model
from keras.layers.core import Dense, Activation
from keras.layers.recurrent import SimpleRNN



def define_model(length_of_sequences, batch_size = None, stateful = False):
    in_out_neurons = 1
    hidden_neurons = 1
    inp = Input(batch_shape=(batch_size,
                length_of_sequences,
                in_out_neurons))

    rnn = SimpleRNN(hidden_neurons,
                    return_sequences=False,
                    stateful = stateful,
                    name="RNN")(inp)

    dens = Dense(in_out_neurons,name="dense")(rnn)
    model = Model(inputs=[inp],outputs=[dens])

    model.compile(loss="mean_squared_error", optimizer="rmsprop")


    return(model,(inp,rnn,dens))
## use the default values for batch_size, stateful
model, (inp,rnn,dens) = define_model(length_of_sequences = X_train.shape[1])
model.summary()
```

Figure 7. Simulation extract of proposed machine learning algorithm.

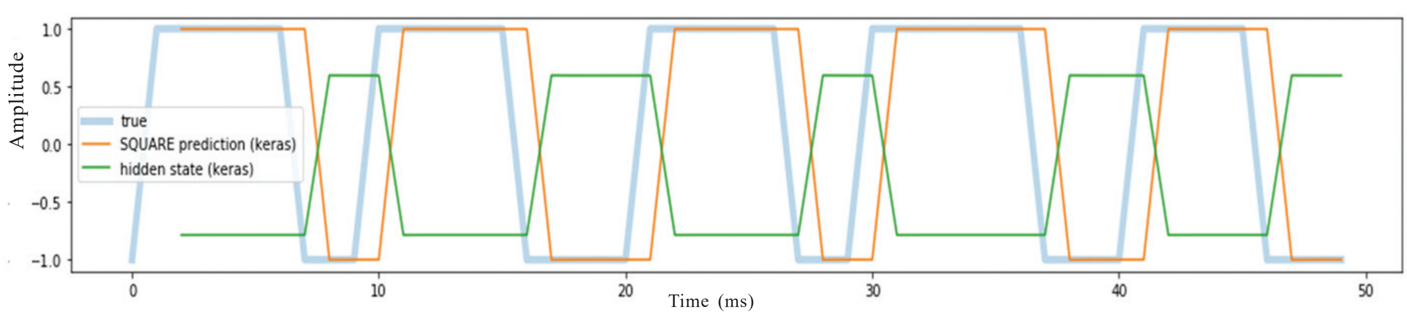

Figure 8. Simulation of the learned and hidden square wave.

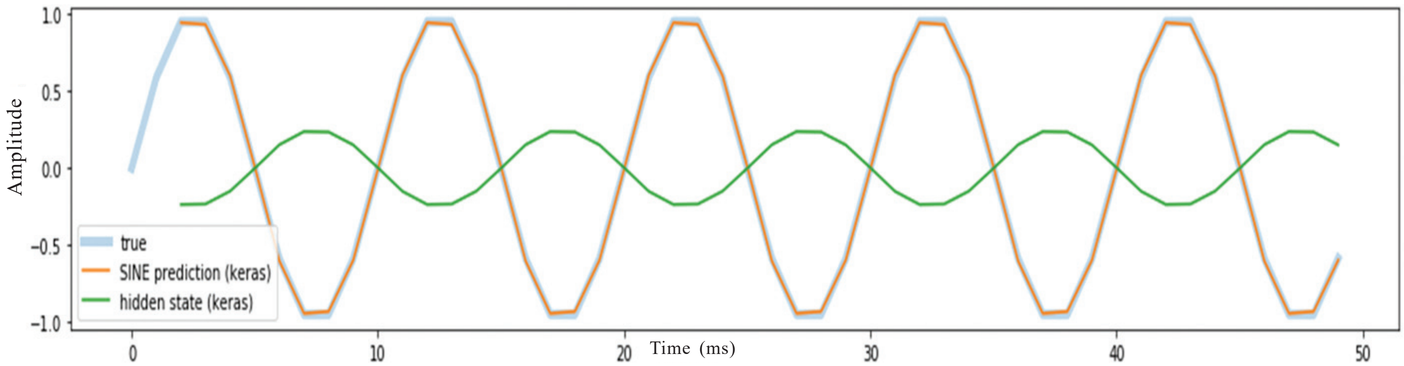

Figure 9. Simulation of the learned and hidden sine wave.

To simulate the proposed machine learning algorithm, the square wave, and sine wave were considered in the algorithm. The simulated machine learning algorithm proposed is presented in Fig. 7. Figures 8 and 9 are the simulation of learned and hidden waveforms, the square and sine waveforms are plotted with the x-axis representing time and the y-axis representing amplitude. Figure 8 presents the square wave, and Fig. 9 presents the sine wave simulations with reference to the neural network's learned waveform at that point in time. The square and sine waves almost match the learned waveforms[21]. The simulations presented here are of very few among many simulations conducted.

5. CONCLUSIONS

Cognitive intelligence is very much required for developing autonomous and dynamic systems. The proposed theory is generic and can be adapted for other systems like radar and communication systems. The second-generation neural network chip is in development with a suitable configuration. The design of machine learning and deep learning algorithms is required for the development of cognitive EW systems. The cognitive machine is the human brain, and proper learning machines will help humanity perform many critical tasks that we cannot execute. In this regard, the requirements of Neural Networks (NN), Recurrent Neural Networks (RNN), Machine Learning (ML), and deep learning techniques are considered for cognitive signal processing in EW applications. The design and simulation of the proposed cognitive signal processing techniques are adapted from learned and hidden sine and square waves presented with the proposed machine learning algorithm.

REFERENCES

1. Saarnisaari, H. & Vartiainen, J. Signal detection with spectrum windows. *Heliyon.*, 2022, 8(7), 1-8. doi: 10.1016/j.heliyon.2022.
2. Zhang, Yang; Si, Guangya & Wang, Y. Modelling and simulation of cognitive electronic attack under the condition of system-of-systems combat. *Defence Sci. J.*, 2020, **70**(2), 183-189. doi: 10.14429/dsj.70.14232
3. Mitola, J. & Maguire, G.Q. Cognitive radio: Making software radios more personal in IEEE Personal Communications., 1999, **6**(4), 13-18. doi: 10.1109/98.788210.
4. Nohara, T.J. & Haykin, S. Cognitive radar information networks for security - Enhancing risk mitigation for reducing operator overload. *In* 2013 IEEE Radar Conference (RadarCon13), Ottawa, ON, 2013, pp. 1-6. doi: 10.1109/RADAR.2013.6585972.
5. Haykin, S. Cognitive radar: A way of the future in IEEE Signal Processing Magazine, Jan. 2006, **23**(1), 30-40. doi: 10.1109/MSP.2006.1593335.
6. Alfonso, Farina; Antonio, De Maio & Simon, Haykin, The impact of cognition on radar technology, 2017, SciTech Publishing, doi: 10.1049/SBRA520E.
7. Antonio, De Maio & Alfonso, Farina. Cognitive radar signal processing. NATO, S&T, STO-EN-SET-216, University of Nepoli, Italy. doi: 10.14339/STO-EN-SET-216-06-pdf
8. Haykin, S. Cognitive dynamic systems: Perception-Action cycle, radar & radio. Cambridge university Press, 2012. doi: 10.1017/CBO9780511818363.
9. Ender, J. & Brüggenwirth, S. Cognitive radar - enabling techniques for next generation radar systems. 16th International Radar Symposium (IRS), Dresden, 2015, pp. 3-12. doi: 10.1109/IRS.2015.7226395.
10. Xiao, Y.; Liu, W. & Gao, L. Radar signal recognition based on transfer learning and feature fusion. *Mobile Network Appl.*, 2020, **25**, 1563–1571. doi: 10.1007/s11036-019-01360-1
11. Jun, Liu; Lee, J.P.Y.; Li, Lingjie; Luo, Zhi-Quan & Wong, K.M. Online clustering algorithms for radar emitter classification. *In* IEEE Transactions on Pattern Analysis and Machine Intelligence, 2005, **27**(8), 1185-1196. doi: 10.1109/TPAMI.2005.166.
12. Xi-Qin, Wang; Jing–Yao, Liu; Hua–Dong, Meng & Yi–Min, Liu Yiu. A method for radar emitter signal recognition based on time-frequency atom feature. *J. Infrared and Millimetre Waves*, 2011, **30**(6), 566-570. doi: 10.3724/SP.J.1010.2011.00566.
13. Sutton, Richard S. & Barto, Andrew G. Introduction to reinforcement learning. MIT Press (Bradford Book), Cambridge, Mass., 1998, **17**(2), 229-235. doi:10.1017/S0263574799211174
14. Dabcevic, K.; Betancourt, A.; Marcenaro, L. & Regazzoni, C.S. Intelligent cognitive radio jamming - a game-

theoretical approach. *EURASIP J. Adv. Signal Process.*, 2014, **171**, 1-18.
doi: 10.1186/1687-6180-2014-171.
15. Crandall, B.; Klein, G. & Hoffman, R.R. Working minds: A practitioner's guide to cognitive task analysis. Cambridge, Massachusetts: The MIT Press, 2006. ISBN-13: 978-0262532815.
16. Mitola, J. & Maguire, G.Q. Cognitive radio: Making software radios more personal. *In* IEEE Personal Communications, 1999, **6**(4), 13-18.
doi: 10.1109/98.788210.
17. Haykin, S. Cognition is the key to the next generation of radar systems. IEEE 13th Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop, Marco Island, FL, pp. 463-467, 2009.
doi: 10.1109/DSP.2009.4785968.
18. Beun, S.L. Cognitive radar: Waveform design for target detection. IEEE MTT-S International Microwave Symposium (IMS), Honololu, HI, 2017, pp. 330-332.
doi: 10.1109/MWSYM.2017.8059111.
19. Kirk, B.H.; Narayanan, R.M.; Martone, A.F. & Sherbondy, K.D. Waveform design for cognitive radar: Target detection in heavy clutter. Proc. of SPIE Radar Sensor Technology XX, 2016, 9829, .
doi: 10.1117/12.2224477.
20. Haykin, S.; Xue, Y. & Davidson, T.N. Optimal waveform design for cognitive radar. *In* 42nd Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, pp. 3-7, 2008.
doi: 10.1109/ACSSC.2008.5074349.
21. Arik, M. & Akan, O.B. Enabling cognition on electronic countermeasure systems against next-generation radars. MILCOM 2015-IEEE Military Communications Conference, Tampa, FL, pp. 1103-1108, 2015.
doi: 10.1109/MILCOM.2015.7357593.

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