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Analysis on Deep Learning Based 5G Wireless Multi-Stage Jamming Attacks

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ABSTRACT: Jamming is a clear danger to the wireless environment and becomes a key issue in raising the number of applications that are important for protection. Implementation of a jamming detector system is important for current networks in order to combat intelligent jamming attacks, which result in a significant loss of performance in wireless networks by the attacker at various intervals. Current detective mechanisms usually use the nodes in the network to obtain network information, which requires overhead costs and node communications. We compare the effectiveness of several model machines for the detection of jamming signals in this paper. We analyze the signal types that define jamming signals and use the same parameters to produce a broad dataset. This dataset was used for training, evaluation and testing of algorithms for machine learning. A random forest, neural system and vector are the algorithms. The results for these algorithms were evaluated and the likelihood of identification, fake warning, error and precision were compared. Machine learning techniques also gain importance on identification and detection algorithms. DCNN has been studied in particular in the area of communication problems, which involve rapid reaction in real-time applications. Deep neural network convolution (DCNNs). The results of the simulation show that jammers can be detected with high precision, high sensory probability and low probability of false alarm by jamming algorithms. The main purpose of this study is to deploy a multi-stage machine learning-based intrusion sensing (ML-IDS) in the 5G C-RAN that detects and classifies 4 types of jamming attack. This deployment improves the safety of C-RAN architectures by minimizing false negative effects.

KEYWORDS: Smart jamming attacks, jammer identification, support vector machine, deep convolution neural network.

I. INTRODUCTION

5G is expected to replace promising higher capacity and less latency for near-future previous generations of mobile networks[1], which allow for applications like cars, the Internet of Things, electronic healthcare, increased reality and urban smart. Thus the internet will be connected to tens of thousands of wireless devices. As with existing network systems, 5G is vulnerable to attacks such as jamming [2] and GPS spoofing [3, 4]. New attacks on these networks, including the primary attacks of user emulation [5] and data sensing, will be made available by cognitive radio [6]. The cyber-security implications of 5G networks are therefore relevant to study [7, 8]. Jammers establish an unintended service denial by sending radio signals that flood the networks for contact with the intention of reducing SNRs of legitimate users.

WSNs have recently expanded their portfolio of technologies, starting with the initial introduction of the battlefield surveillance systems, Include areas such as emergency aid, weather prediction, protection and plant automation applications. Without an existing infrastructure, WSNs consist of small and cost-effective sensor nodes. The data is frequently used for the detection, sorting, transmission and reception of information from the region in advance. The structure (topology) and environment of hundreds to millennia of sensor nodes are defined by the standard WSN. By placing sensor nodes [1] in the setting used WSNs can be categorised structurally. These nodes can have the same skills, while others can have different skills according to the architecture. There is a flat, hierarchical and clusters of the three main forms of structures of the WSN[3]. The requirements for the operation of sensor nodes in WSNs can also be subdivided into the following five classes:Underground WSN, terrestrial WSN, submarine WSN, WSN, mobile multimedia[3]. Sensory nodes also use in a WSN and are specified with resource limitations in distance, difficult and inaccessible areas, including limited energy, Bandwidth restriction and contact with limited range. These sensor nodes are vulnerable to different attacks on defense, including service denial and the vulnerability of wireless media (for example, open and shared) (DoS). On 21 October 2016 a recent DYN attack was reported[4] by a major DNS provider. A Mirai malware botnet that infects around 100,000 malicious terminal nodes was used to attack Dyn DDoS. This

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distributed DoS type has been defined by experts as the most devastating DoS attack so far and covers approximately 1,2 tbps.

The detection of jamming attacks included noise, busy channel ratios of the packet transmission and overall inactive time. More resources are needed and only serve as a stopover for most of the previously cited techniques[11]. You may detect the connection status as below, but sometimes the cause of the service failure cannot be found. Furthermore the likelihood of false alarm is relatively high. For training and testing classification models, you need specific algorithms. Selection of features and learning curves are frequently overlooked, as one of the most critical processes in the development of machine learning detection techniques. Strong and fast detection techniques are therefore required for more effective detection of jamming attacks. This article proposes that the transmitting connection state of a transmitter and a recipient be identified using machine learning to verify that they are attacked.

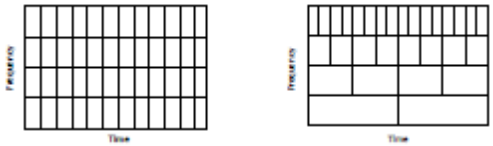

Figure 1: An exemplary graphical representation of (a) short time Fourier transform (STFT) and (b) wavelet transform.

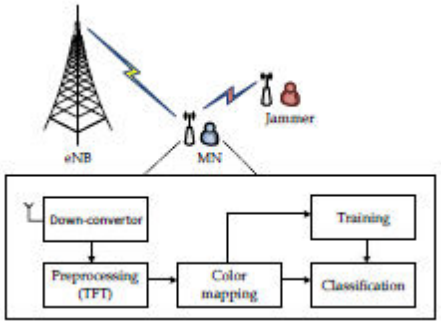

Figure 2: A base station (eNB), node (MN) and a Shoot in a cell of LTE.

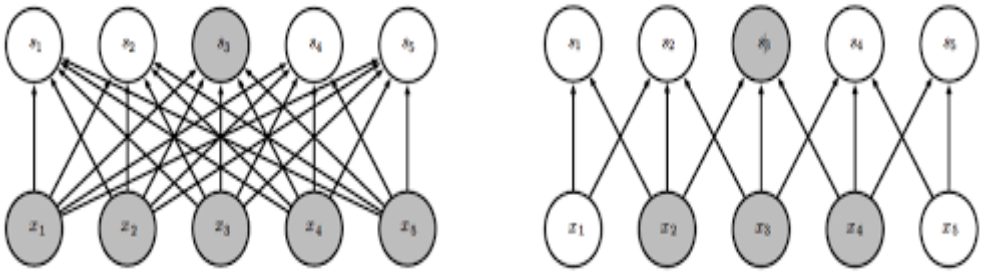

Fig 2.1: Traffic density estimation using CNN.

In comparison, wavelets are finite, located on a time-frequency plane, which allows for the efficient identification and detection of intelligent jammers in the time-frequency plane. A temporary signal changes are monitored by adding a rectangular window prior to Fourier STFT transformation. The signal resolution in all positions is the same time and frequency as the rectangular window of STFT. As shown in Figure 1, different window sizes in wavelet transforms provide the different signal locations with multi-resolutions, unlike STFT. This helps us to have an adaptive resolution property to adjust signals resulting from intelligent jammers. We consider the LTE-downlink channel jamaging scenario, which captures downlinking channel observations through a permanent processing of received baseline signal in a stationary monitoring node (MN). MN is synchronised and the transmission from the base station (eNB) is targeted by a fixed jammer, as in Figure 2. Please notice that MN has no previous knowledge of the jammer attack.

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As detailed in the following section, jammer identification is usually based on the network measurements or signal characteristics. On determining the attack type, identification algorithms may use different probabilistic approaches. Machine learning techniques also gain importance on identification and detection algorithms. In particular, deep convolutionary neural networks (DCNNs) have been studied in various communications issues which require fast response in real-time applications. The main application areas can be listed as localization, modulation classification, channel decoding and waveform recognition.

II. LITERATURE REVIEW

Jamming attacks with the wide use of WSNs send malicious radio signals have been studied in the literature, to interrupt legitimate communication and to consume energy. This is important because of their design, aggressive implementation and insect routing protocols, this kind of attack is vulnerable to sensor nodes.

In order to detect jamming attacks at base stations, Mistra et al. are proposing a centralised approach, The use of each network sensor node's three inputs. Complete packets received are these inputs, the number of packets dropped and the signal received (RSS). The base station tracks energy during a jamming attack in order to detect RSS and RSS shifts. In the calculation of the terminal jamming inference (PDPT) system and of the signal noise ratio (SNR) inputs, the base station will use these values. The jamming index ranges from 0 to 100 and is used to calculate disturbance rates from non-jamming to total interruptions.

Strasser et al. defined the source of bit errors in each packet by examining the RSS for reactive jamming on reception sensor networks. This technology focused on default skills and limited node cabling. Effectiveness of the identification of complex reactive attacks without more overhead is demonstrated by the experimental results on Chipcon Radios. Spuhler et al. suggested an approach for determining the probability of packet transmission during packet transfer synchronisation in order to identify complex reactive jamming attacks. It ensures the use of chip mistakes on the preamble symbols by calculating the likelihood of packet transmission to jammers directed at the physical layer of the WS N.

Guan and Ge have suggested a distributed method for the detection of multi-channel jamming in WSN. In its course, the Markovi Chain was formed in a piece by means of multiple measurement channels to detect random attacks, Complex of two-tier MDJA switching. Each Markov chain state space corresponds to the potential jammers. On an elevated stage, there are two differences in the probability of transition, namely stochastic changes and the average time change for determinists. In her work, Cordero and Lisbon have studied a WSN with a non-cooperative two-player problem that has heterogeneous jamming. The role focuses on signal interferences and the receiver's noise ratio and the second-order cone programme solves the game problem. Numerical results suggest that when a detection technique is configured for the jamming attack, the distance between network elements should be clear.

In order to tackle jamming attacks in WSN, Mpitziopoulos and Gavalas are proposing a hybrid hopping frequenz Spektrum (FHSS) and a direct sequence spreading spectricum (DSSS). The technology proposes that a channel sequence be created with a key known only to nodes and sinknotes of 5 G Hz 5-GHz. Each of these channels uses 16-bit modulation of the pseudo-noise code from the same key used in the generation of the FHSS channel. The results of the simulation show, in comparison to ordinary network sensors, that Ares' nodes in a jammed WSN environment can ensure a satisfactory packing rate.

Alnifie and Simon suggested a fully distributed protocol for the evacuation of data from the jammed areas as a result of a radio jambming dos attack inside a WSN, the MULti-channel Exfiltration PROtocol (Mulepro). It works by dynamically assigning the attacker to the nodes in the jammed area. For this reactive jamming attempt, robust WSN protocols like AODV DSR and the new MPH were tested. The authors then proposed that the AODV-M, DSR-M and MPH-M protocols should be modified; which ensure the isolation of the node and modify the routing Protocols to avoid isolated nodes when attacks were detected by the nodes in the detection algorithm.

III. METHODOLOGY

The classification issue for which the classifier must determine is to define a jamming attack in this document: a jammer loses the connection or another cause loses the link. The explanation why this problem is solved with machine

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learning theory is the effectiveness of this theory, which solves complex problems over a reasonable period of time and uses reasonable funds. The selection of suitable features is important to create an effective machine learning algorithm. Several characteristics for the existence of jamming attacks have been chosen in this work. It is not sufficient to detect a single parameter jamming attack. Furthermore, analytical relations between these parameters and the state of the connection can be complicated to find. Machine learning theory is used for these purposes detect jamming attacks by finding an empirical relationship among those four metrics.

A. Jamming attacks model

Blowjob attacks target cross layer layers of both the physical and wireless network. During jamming signals that hold the channel occupied, the desired communication between an A-based transmitter and a B-based recipient is interrupted. In case of a longer channel occupancy of jamming signals, a service denial may be established. If at position A the signal is marked by x(t), and the signal received at point B is marked with y(t), then the sign at position B in absence of the jammer signal is marked by This signal received at location B

$$y(t) = x(t) + n(t) \qquad (1)$$

is the signal and n(t) is the transmitter-to-recipient white additive noise; which is the signal that is required for x(t). And y(t) are transmitting this signal. The jammer falsifies the signals they want to provide a signal for the channel to be flooded. If the jammer signal is present, the receiving signal at position B is then indicated by:

$$y(t) = x(t) + x_j(t) + n\,(t) + n_1(t) \qquad (2)$$

Noise is the path from receiver to location of jammer, Jammer and n1 where xj(t) is (t). This problem can also be considered a problem of classification if the input signal is allocated to one of the input classrooms of the student: the received signal would be the desired signal.

B. Feature selection

The jamming detection criteria include poor packet ratio, packet propagation ratio, achieved signal level and simple channel analysis. In order to calculate those steps, all communications come with network interface card and diagnostic mechanisms. The low packet ratio is one of the major elements for detecting jamming. The percentage of wrong packages obtained is indicated. It is calculated at the end of the receiver and indicated as

$$PR = \frac{Number\ of\ erroneous\ received\ packages}{Total\ number\ of\ received\ packages} \qquad (3)$$

$$\text{PDR} = \frac{Number\ of\ package\ delivery\ correctly}{Total\ number\ of\ transmitter\ package} \qquad (4)$$

The signal strength obtained, RSS, tests the recipient's surrounding force. It is high if no attack is present; however, if the channel is subject to some attack, it decreases. RSS can be represented on the recipient

$$RSS = \frac{P_t * G_t * G_r * (ht^2 * hr^2)}{d^4} \qquad (5)$$

$$RSS = K\frac{P_t}{d^4} \qquad (6)$$

C. Machine Learning Algorithms

Below is an overview of each of the algorithms of the machine learning.

1) Random forest

The random forest is a hierarchical system for classification consisting of several decision-making trees. The test data is categorised according to their characteristics by sorting trees. There is a single node and multiple branches in each decision tree. The option node is the function of the test data, with branches that represent a predictable node value. The aim is to prevent overcrowding behind the use of several trees. Method variance will be minimised, and the final model will potentially be more accurate. In order to be able to random forrest classification, the total number of trees to be formed should be fundamental parameters and decisions relevant to the tree decision makers such as minimum division and division requirements.

Combined these trees shape the overall estimate to train the forest using:

$$\bar{r_n}(X, D_n) = E_\theta[r_n(X, \theta, D_n)] \qquad (7)$$

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where $E_\theta$is the random parameter expectation, conditionally, on X and the D n data set. When the forest is conditioned, the following equation can be used to predict each tree independently for output values.

$$f_n^j(x) = \frac{1}{N^e(A_n(x))} \sum_{\substack{Y_i \in A_n(x) \\ I_i = e}} Y_i \qquad (8)$$

Where x is each tree's query point. The forest combines each tree's predictions to obtain the final value:

$$f_n^{(M)}(x) = \frac{1}{M} \sum_{j=1}^{M} f_n^j(x) \qquad (9)$$

2) Support vector machine

The vector support offers a data-separation hyperplane in two classes. The kernel selection defines the separation line of the two groups. Various kernels, for example linear kernels, radial foundation, quadratic and cubic kernels, can be used with this model.

3) Neural Network

A Neural network is a biological model for the study of observational evidence by a computer. It has demonstrated its capacity to learn and adapt to various subjects, including the processing of images, in various areas of research. The neural network includes one or more hidden layers and an output layer. One or more neurons are in each book. A neuron consists of an activation mechanism that interacts with various layers of the other neurons. Each relation is connected to a starting weight, and the neural network attempts to find the optimum weight set in the learning process to minimise the error between the hypothesis function and the dataset mark. The two main principles, propagation and reverse propagation are part of any neural network.

1. The proposed system model

This section introduces the proposed system model by first showing the deployed architecture and then justifying the classifiers chosen.

A. The Deployment Architecture

Figure 3, with its mesh topology, demonstrates the architecture of the suggested Low Energy Aware Cluster Hierarchy (LEACH) routing protocol, ML-IDS in CRAN architecture. The LEACH clustering protocol for WSNs is adaptive and self-organized and is based on its simplicity and low energy. The base station (BS) is assumed to be fixed and situated away from sensor Nodes by LEACH. The LEACH protocol's principal idea is to create cluster nodes that distribute energy across all network nodes. There is also a cluster head (CH) in each cluster, which collects the data that the sensors obtain in their cluster and then transmits them to the BS.We have a range of antennas at the BSs that provide greater coverage geographically.

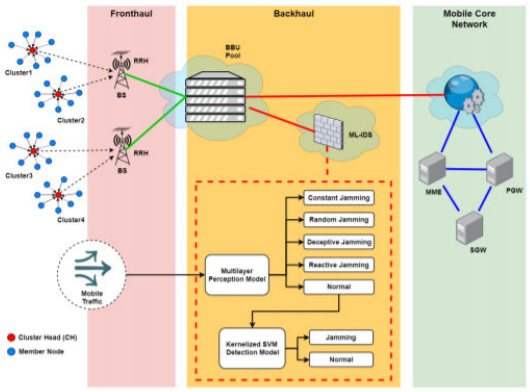

Fig. 3: Architecture for C-RAN environments to deploy the proposed ML-IDS.

The proposed ML IDS collects and uses a Multilayer Perceptron to capture mobile traffic between clusters and Fronthaul (MLP). Our model categorizes traffic into five different categories, namely continuous interruption, random jamming, disappointing interference, reactive interference and natural trafficable. If labelled as standard by MLP, a Kernelized Support Vector Machine can process the traffic again (KSVM). The aim of adding a KSVM after the MLP

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is to reduce false negatives generated by the MLP. The machine decides that the condition is normal in a false negative, when an assault is in fact taking place.

B. The Implemented Classifiers

Together with two classifiers, four forms of jamming attacks have been detected in the BBU Pool. Therefore, the second one will detect it if an attack with the first classifier is skipped. MLP is a deep learning algorithm, the first classifier. MLP consists of an interconnected neuron system as shown in Figure 4 that is a type of non-linear mapping of input and output vectors.

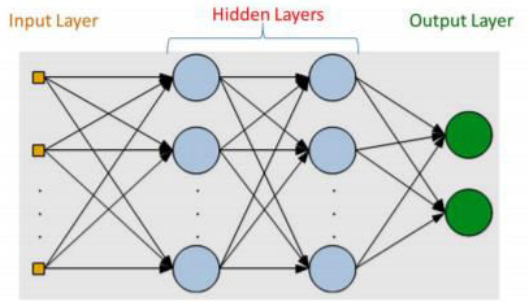

Fig. 4: A multilayer perceptron with several hidden layers

MLP is selected because of the huge number of input vectors (we have 374661 in our case) and the stochastic gradient drop is therefore always the best option in terms of speed, capacity and control (especially for classification). Because of the versatility that it can be applied to various kinds of data, MLP was chosen among all the profound learning algorithms (CNN, RNN, LSTM, DBM...).

The KSVM is a powerful binary classification. The second algorithm is introduced.Known that blowjob attacks in a low-dimensional space are not linearly separable, KSVM deals with these situations when using a kernel function. This function maps the information in another place where the attacks can be divided through a linear hyperplane. Figure 5 shows this operation. The kernel trick is named as the kernel function converts the data into a larger dimensional space to allow a linear separation.

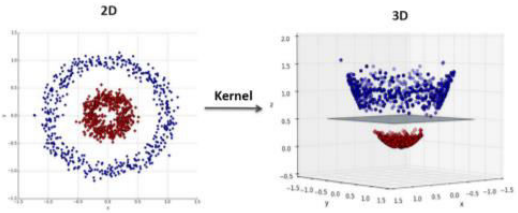

Fig. 5: Non-linear classifier using Kernel trick

The so-called decision limit or hyperplane that separates classes has weighting coefficients from the vector W, which must be estimated. In order to achieve our limitation the KSVM classifier tries to optimize the difference between this vector W and the closest point (support vectors). This means that the following equation is minimized:

$$W(\alpha) = -\sum_{i=1}^{l} \alpha_i + \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j x_i x_j$$

Subject to:

$$\sum_{i=1}^{l} y_i \alpha_i = 0$$

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C. Adversarial Deep Learning-based Jammer

The exploratory attack applied to [8] text grading and [9] image grading can deduce a machine learning (including profound learning) classification. In the previous works the fundamental concept was to call the goal classification system and obtain a number of sample labels and then to use deeper learning to train a functionally equivalent classifier. When the same sample has the same names, two classifiers are functionally identical. However, the layout of this paper cannot be applied. The sensing results at T and J will be different due to differing positions, the random channel gain and the random noise.That is, T as well as J feel a Gaussian N0 noise while the channel is idle, but because of different realizations the value can be different. T will sense N0+IT and J will feel N0+IT if the channel is busy.

The channel status and the actions of T are in four cases:

1) the channel is idle, T broadcasts,
2) the channel is busy, T does not transmit,
3) the channel is idle, T does not transmit and
4) the channel is busy, T transmits

IV. RESULTS AND DISCUSSION

To define jamming attacks for testing machine learning models, 4 different parameters were used. A real simulation environment has been carried out in both cases to gather measurements from these parameters: the link is attacked and the link is not attacked. The data set was divided into n-folds using the cross-validation technique for training and evaluating the model. To divide the date into N equal sample number, Cross N-fold validation was used. Machinery learning algorithms have been trained to determine the efficiency of certain devices in the dataset with various folding sizes, such as 2, 5, 10, and 20.

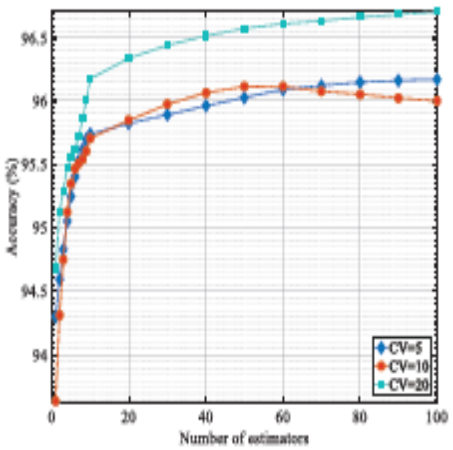

Fig. 3. Accuracy as against the number of random forest estimators with different k-fold number of CV=5, 10 and 20 cross-validation.

We have done many experiments, and we have provided examples of Fig effects. Fig 3 To 6. The accuracy of random forest classifications versus the number of various cross validation fold calculators is shown in Figure 3. This figure shows that the classification accuracy for all K-folds, 5, 10 and 20 is exponentially improved, depending on the number of estimators, for numbers less than 60. The figure is shown in below.

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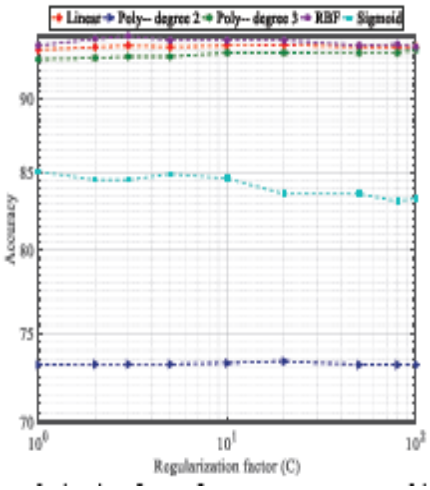

Fig. 4. Accuracy Vs vector support regularisation factor.

We tested the exactness of various kernels and regulatory parameters of C in order to find the best vector model to support it. Figure 4 shows the precision of the classification function for linear, quadratic, cubic and radial kernels of regulating factor 'C,' and this figure shows that the influence of the "C" factor does not affect the accuracy significantly.

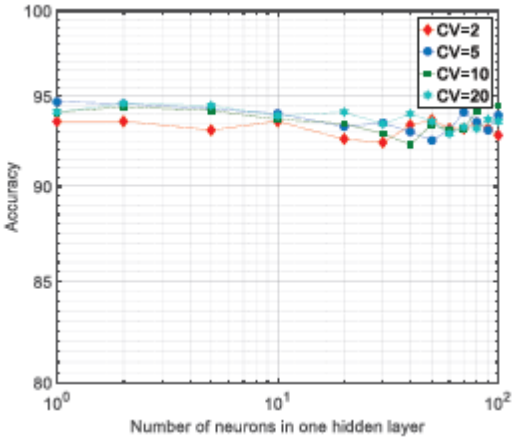

Fig. 5. Precision of the neural network Vs number of neurons in the cached layer.

Figure 5 displays the concealed neural layer of a number of undisclosed neurons, due to their precision in the rating feature for many k-folds of cross validation. There are no major implications for the number of hidden neurons and cross invalidation methods, as the rating remains approximately 94% exact, but with one neuron 5 times and 100 neuron 10 times cross-validation the maximum.

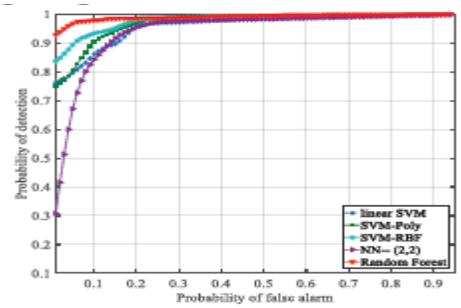

Fig. 6. The probability of false alarm detection Vs

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6 is shown in linear Pd Vs. Pfa, 2nd grade SVM;; 2-neuron neural network, and 100 approximate random forest. You can see that Pd fits with Pfa.

Defense against Unknown Jammer Types

Random attacks are not supposed to be addressed by the protection system. T don't know what) jammer shape is targeted. Therefore, we take another step to start the protection algorithm of the transmitter to mitigate attacks with a defined defence level and then gradually increase or decrease the defence level in response to its output changes calculated with the ACK messages received.

The optimal protection scheme must have pd > 0. As described above, J applies an attack based on deep learning. If J applies an attack dependent on randomness or sensing, the optimum security regime should be pd = 0. T doesn't necessarily know the J attack scheme, so we must establish a general approach to determine the best pd value based on the results achieved. The linear search can be a simple approach, by comparing more than +0.00% points (e.g. 0%), 10% (·100%) and evaluation of an optimal approach to pd.

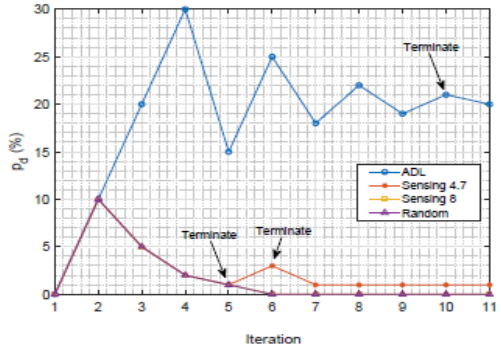

Fig. 7. Looking for the best pd value in the protection mechanism of the transmitter.

In order to provide greater granularity, T further examines the present value by looking for a better pd value and repeats this process until the desired granularity or an improvement has been achieved.In Table 1 for example, the best pd for T's performance is 20%. T check even approximately 20 percent with a smaller phase size of 0.182 or 0.202 respectively, i.e. 15 percent or 25 percent Thus, pd = 20% is still the highest. T repeats this process and ultimately concludes that the best alternative is to pd = 20 percent. Pd = 0 percent offers the optimum protection for sensing-based jammers (with Ţ = 3.4) and random jammers.

TABLE 1 RESULTS FOR DEFENSE SCHEME AGAINST ADVERSARIAL DEEP LEARNING-BASED JAMMING ATTACK.

Pd	Jammer error probabilities		Transmitter performance	
	Misdetection	False alarm	Throughput (packet/slot)	Success ratio
0% (no defense)	4.18%	14.53	0.050	6.25
10%	17.53	23.68	0.132	17.98
20%	32.80	33.33	0.216	31.6
30%	33.92	38.25	0.194	30.4
40%	35.83	37.31	0.178	31.6
50%	38.97	38.33	0.170	32.32

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TABLE 2 RESULTS FOR DEFENSE SCHEME AGAINST SENSING-BASED JAMMING ATTACK WHEN _ = 3:4.

Pd	Jammer error probabilities		Transmitter performance	
	Misdetection	False alarm	Throughput (packet/slot)	Success ratio
0% (no defense)	11.18%	12.53	0.070	7.25
10%	18.53	20.68	0.232	27.98
20%	35.80	30.33	0.316	41.6
30%	35.92	35.25	0.394	20.4
40%	38.83	35.31	0.378	41.6
50%	40.97	34.33	0.270	42.32

This search is shown in Figs. 'Sensing 3.4' refers to S = 3.4 sensor-dependent jamming and 'Random' refers to random jamming, where 'ADL' means jamming based upon deep opponent learning. "Terminate" means the end of T's quest for the best pd.

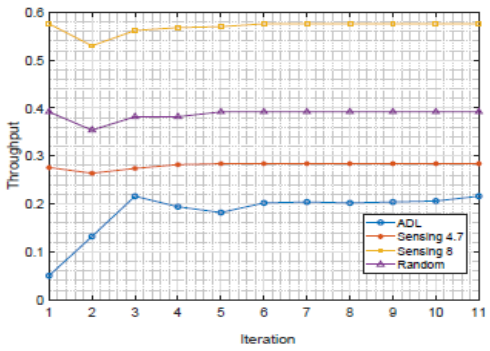

Fig. 8. The throughput achieved during the search for the best *pd* value.

T begins with the next iteration using this best pd value. The 500 slots are the equivalent of each iteration.
70 percent of training data and 30 percent evaluation data were split for the WSN-DS. The data separation is shown in

Table 3. TABLE 3: Number of documents used in datasets for training and research.

Class	Number of records used in dataset	
	Training set (70%)	Testing set (30%)
Normal	238103	101963
Constant jamming	10233	4363
Random jamming	6960	3089
Deceptive jamming	4650	1988
Reactive jamming	2316	996
Sum	*262262*	*112399*

V. CONCLUSION

In the present paper we have proposed the use of a new intrusion detection method for learning machines that detect four different forms of jamming assaults in Cloud Radio Access Networks (C-RAN) (MLIDS).In a hierarchy structure, deep learning uses cascading levels to conduct data processing, resulting in substantial results in unattended function learning and pattern recognition areas. Inspired by the profound methods, we believe that in order to investigate the current method of deep learning in the detection of attacks, profound education is needed for network security. Recent methods are analysed, categorised by different profound learning strategies and compressed by the most representative

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methods.5G technology equipped with a millimetre wave band to be resistant to jamming attacks. However, frequencies below 6 GHz, easily targetable by jammers, are also planned. To prevent such attacks, intelligent jamming detection techniques are required. We discussed the latest techniques of detection of jamming in this paper. There have been studies and comparisons into the efficiency of different machine learning modes for jamming attack. A large data package to train, validate and test random forests, vector supports and algorithms for the neural network has been developed and feature extraction and function selection. We have used a cross-validation approach to measure the efficiency of these models on the basis of certain parameters. For learning, we gave curves. The system model proposed is a wavelet preprocessing step and an in-depth classification of learning. The effectiveness of the transformative approach is clearly observed even when smart jamming takes account of an LTE downlink communication scenario. Considering different pre-processing methods, the superior performance of DCNN is observed.

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