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Machine Learning Aided Electronic Warfare System

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ABSTRACT In this article, a machine learning aided electronic warfare (EW) system is presented and the simulation results are discussed. The developed EW system uses an automatic decision tree generator to create engagement protocol and a fuzzy logic model to quantify threat levels. A long-short term memory (LSTM) neural network was also trained to predict the next signal set of multifunction radars. The simulation results demonstrate the effectiveness of the developed EW system's ability to engage multiple multifunction radars.

INDEX TERMS Electronic warfare, machine leaning, fuzzy logic, decision tree, ID3, Long Short-Term Memory (LSTM).

I. INTRODUCTION

An electronic warfare (EW) receiver is designed to detect and combat hostile radars. Rapid advances in cognitive and multi-mode radar systems make tasks for EW systems more challenging than ever. During a mission, an EW system might encounter voluminous uncertainties and radars, some of which can change operating parameters when necessary, further complicating an EW system's task. One possible solution to this issue is Machine Learning (ML) and EW researchers have successfully applied ML for some EW applications like signal classification [1], [2]. One goal of applying ML in EW is to develop a cognitive EW system that can reason through different scenarios and choose optimal countermeasures. This subject has become a popular research topic. In recent years, besides magazine articles on cognitive EW systems [3], more reports on cognitive EW systems ranging from general system architectures to specific systems designed for training purposes or signal classification can be found in open academic literatures [4]–[11].

In this article, an integrated machine learning aided EW system consisting of EW decision making, automatic navigation, and threat level assessment is presented. A comparable research effort reported in open literature is an autonomous artificial intelligence simulator called TacAir-SOAR developed by researchers at the University of Michigan to simulate a pilot's reactions in a battlefield. In their synthetic theater of war battle simulator, TacAir-SOAR executed 5,200 rules for the different situations experienced by the pilots that were interviewed, which determined how the model would transition through its states [12], [13]. Therefore, all the rules are predetermined and might not be altered in real-time.

On the other hand, the decision-making protocol used in the system proposed in this paper is based on a decision tree that is automatically generated from simulated EW encounters. As the decision tree is automatically created through the training data, this approach is more flexible and has the potential for automatic in-flight updates. The developed EW system was tested within a software simulated environment against multiple multifunction radars, and it achieved satisfactory results. The potential usage of a long short-term memory (LSTM) neural network for predicting a multifunction radar's next move is also investigated in this project.

EW environments are constantly changing, which is why machine learning and cognitive agents are being utilized. Cognitive electronic warfare systems seek to autonomously conduct tasks that would otherwise require human intervention. Cognition is defined as the knowledge required to act or process an event [14]. Fuster's paradigm of cognition states that cognitive agents have the following abilities:

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perception/action cycle, memory, attention, intelligence, and language [14]. There are four primary tasks for cognitive EW systems: target detection, target acquisition, target tracking, and platform guidance [15], all of which are achieved by the developed system. Therefore, the accumulation of machine learning models can be considered a cognitive EW system and the system presented in this article is a step toward a fully cognitive EW system.

The rest of this article is organized as follows. Section II provides an overview of the problem space. Machine learning techniques used in this study are presented in Section III. The proposed EW system is detailed in Section IV. Simulation settings and results are presented in Sections V and VI respectively. Section VII concludes this article.

II. PROBLEM OVERVIEW

While there exists a rich problem space in the field of machine learning for radar signal classification, the presented work focuses on the handling of labeled signals. It is assumed that an EW receiver chain has detected and deinterleaved radar signals into pulse descriptor words (PDWs). From that point, a stream of PDWs and associated geolocations are fed into the proposed EW system and has a corresponding confidence value for each emitter type. It was assumed that a robust geolocation module is available on the platform. It was also assumed that small deviations in the emitter geolocations would not create a significant impact in the decision-making process; therefore, the true emitter geolocations were used throughout the simulations. The emitters were randomly placed between the pilot and the goal location for each simulation. However, the PDW classification is imperfect. Therefore, the radar signals can be misclassified, and a higher confident level is intentionally assigned to the false PDW (with wrong signal classification but true location); consequently, the EW system will most likely combat the misclassified emitter initially. As the result, due to applying the wrong jamming signal, the pilot's location is revealed to hostile emitters at the beginning of the encounter regardless of their positions and the EW system needs to correct this mistake. It will be a difficult situation to handle; hence, the impact of a false geolocation was ignored because a more difficult case was simulated.

The problem faced by the EW system, then, is to determine the best course of action given the imperfect radar observations from multiple radars, and a goal location. In the simulated scenarios, the EW system exists on a mobile platform located within a two-dimensional space, along with some number of stationary monostatic radar emitters. The goal of the EW system is to maximize the platform survivability, while successfully maneuvering to a goal location on the 2D grid. The EW system determines the appropriate set of actions to maximize survivability. The set of actions that can be recommended by the EW system at each simulated time increment is $\mathrm{act_{EW}} = \{\text{modify trajectory}, \mathrm{EA_{i,j}}, \text{nothing}\}$, where $\mathrm{EA_{i,j}}$ is Electronic Attack (EA) i applied to radar emitter j. An optimal solution for a scenario would therefore attempt to arrive at the goal location, while avoiding detection by adversary radars through physical distancing, minimizing emissions, and employing effective active countermeasures to minimize radars' tracking capabilities.

III. MACHINE LEARNING TECHNIQUES

This section provides a brief description on the machine learning techniques that were investigated for this project.

A. ID3 DECISION TREE [16]

A decision tree is a supervised machine learning technique commonly used for classification or decision-making tasks. Based on the provided training data, decision trees are an efficient method to determine the most suitable actions in the most efficient way. There are a variety of decision trees that each offer its own benefits and drawbacks. In this project, the ID3 algorithm is applied due to its simplicity. The basic concept of the ID3 algorithm is as follows. Assuming that the training data consists of multiple training attributes (i.e. features) and a single class in the following format $[\mathrm{att}_1, \mathrm{att}_2, \mathrm{att}_3, \ldots, \mathrm{act_{EW}}]$, in which att_i represents a specific feature of the radar emitter such as distance, mode, and etc., and act_{EW} is a suggested EW action. Assume there are M sets of training data and the entropy of act_{EW} in the training data is defined as

$$Entropy\,(act_{EW}) = \sum\nolimits_{i=0}^{K-1} p\,(act_{EWi})\, log_2(p(act_{EWi})) \quad (1)$$

where $p\,(act_{EWi})$ is the probability that the countermeasure (act_{EWi}) is taken and K is the number of available countermeasures. Assuming that the data can be split into two groups based on a specific radar feature. These two groups are referred to as group A and B. The act_{EW} entropy of each group is calculated using (1) and the entropy of this split is then defined as

$$Entropy_{split} = \frac{n_A}{M} Entropy_A + \frac{n_B}{M} Entropy_B \quad (2)$$

where $Entropy_A$ is the act_{EW} entropy of group A, $Entropy_B$ is the act_{EW} entropy of group B, the number of data sets in group A is n_A, and the number of data sets in group B is n_B. An ideal split creates a split entropy much smaller than the original entropy. The ID3 algorithm splits the data based on the feature that reduces the entropy the most. This process is repeated to separate the data until the entropy reduction is smaller than a predefined threshold, or until the decision tree reaches a predefined depth threshold.

B. FUZZY LOGIC [17]

Unlike Boolean logic, whose discrete truth value is {0, 1}, the truth value of fuzzy logic is a continuous number in the range of (0, 1). The purpose of fuzzy logic is to analyze and reason with imprecise information. For example, the distance between a radar system and a platform can be classified into three classes: {close, medium, far}. The membership function for these three classes vs distance (km) is shown in Fig. 1. As shown in Fig. 1, the range of the membership function for each class is (0, 1) and there is overlap between the different classes. Fuzzy logic applies AND, OR, etc. concepts to extend Boolean logic operation. Fuzzy logic has been applied for EW applications such as determining countermeasure and allocating resources for electronic attack [18], [19]. The fuzzy logic emitter threat model of the proposed EW system fuzzifies the distance to the emitter and the PDW classification confidence using membership functions similar to the one shown in Fig. 1. After applying fuzzy logic operation upon fuzzy sets, the fuzzy logic emitter threat model defuzzifies the result and outputs a numerical emitter threat level. In the proposed EW system, fuzzy logic is applied to estimate a radars' threat level based on its operation mode and distance, thus providing the EW system a priority for which emitter to engage. An additional fuzzy logic model is used to quantify the general EW environment threat level based on the modes of all the detected radars and the closest distance to the EW system platform.

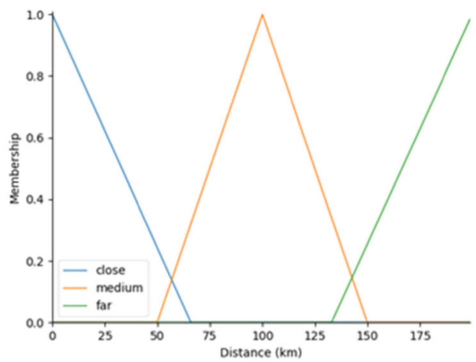

FIGURE 1. Fuzzy logic membership function examples.

C. LONG SHORT-TERM MEMORY NEURAL NETWORKS [20]–[22]

Long Short-Term Memory (LSTM) Neural Networks are a supervised machine learning technique used to analyze sequential data. Unlike traditional feed-forward neural networks, which only consider the current set of information, LSTM networks can consider previous information through the integration of LSTM cells within a neural network. An example LSTM network unrolled in time is depicted in Fig. 2. As shown in Fig. 2, at each given time, the LSTM network generates an output based on the current input, state, and carry over memory. State and carry over memory are also updated based on current input, current output, and previous carry over memory. With a sequence of training data, the LSTM is unrolled in time (as shown in Fig. 2) and trained using back propagation through time. LSTM has been applied to determine the mode of multifunction radar [23]. In this project, an LSTM model is used to predict a multifunction radar's next operating signal set based on previously recorded data.

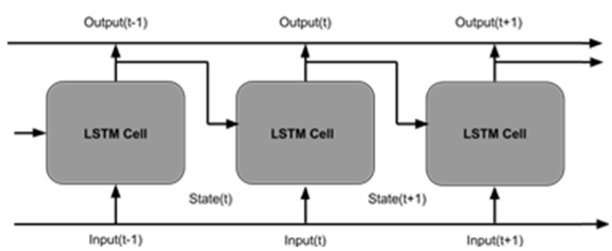

FIGURE 2. A simple LSTM diagram [22].

IV. PROPOSED EW SYSTEMS

The proposed EW processing system framework and supporting simulator framework are depicted in Fig. 3. The Pre-Classified Signal Analysis Unit estimates the radars' signal set and current mode (scan, acquisition, track, or fire) based on PDWs and calculates their distances to the platform. It is worth mentioning that the Pre-Classified Signal Analysis Unit is deliberately set to misclassify certain signals in order to test the robustness of the developed decision framework.

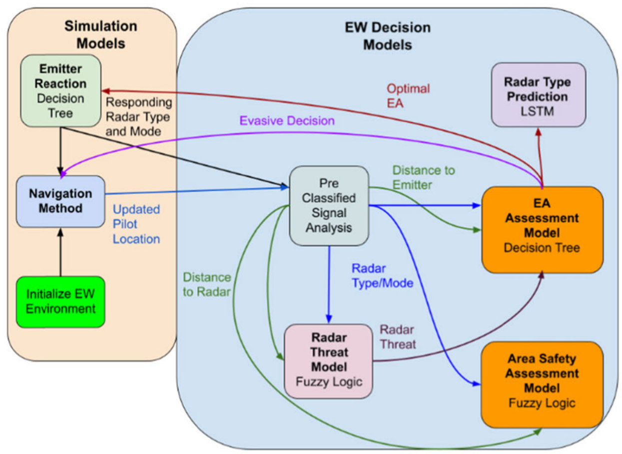

FIGURE 3. Proposed EW system and simulator setting.

The Radar Threat Model determines the threat level of each of the observed radars based on its distance and mode. The Electronic Attack Assessment Model ingests all available information and utilizes a decision tree to determine an appropriate action. This decision tree was trained with previously collected results for which EA was successful at jamming a given emitter type. The specific training parameters are depicted in Table 1. It is assumed that the EW System can only recommend one active countermeasure at any given time. Therefore, when there are two hostile radars present, the platform might perform countermeasures against one and be forced to avoid the other.

There are two units in the EW system used for analyzing data that do not contribute to deriving EW actions. The Area Safety Assessment Model is used to determine the platform's safety level based on the presence of hostile radars. The Radar Type Prediction Model is an LSTM network that is trained with a sequence of radar emissions and applied countermeasures. It is used to predict the radar's next operating signal characteristics. This unit is included in the simulation to test

TABLE 1. EA decision tree training parameters.

Training Parameter	Description
Emitter 1 Type	Emitter type for a given location.
Emitter 1 Mode	The mode of the emitter at a given location
Emitter 1 Threat	Individual emitter threat level from fuzzy logic model.
Distance 1	Distance to emitter location 1 (km).
Emitter 2 Type	Emitter type for second location.
Emitter 2 Mode	The mode of the emitter at second location
Emitter 2 Threat	Individual emitter threat level from fuzzy logic model.
Distance 2	Distance to emitter location 2 (km).
Action	Action that was previously successful for the given situation.

the effectiveness of applying an LSTM for radar behavior prediction purposes. However, it is reasonable to assume that after several missions, the Radar Type Prediction Model can be used to predict a radar's next move and it should be integrated into the EW decision-making process.

The Simulation Models block of Fig. 3 represents the models driving the simulation outside of the EW system. In the simulation, it is assumed that there are two stationary multifunction radars, whose modes consist of scan, acquisition, track, and fire. The transition between modes is based on the platform's distance to the radar and the duration that the radar is in the current mode. If an appropriate active countermeasure is applied by the EW system, then the radar loses its target track and switches back to scanning mode. If an incorrect countermeasure is applied, then the radar reduces the number of required cycles for advancing to the next mode. In other words, the radar transitions closer to fire mode as an incorrect EA exposes the platform. Once a radar determines that it has been jammed, then it switches to a different set of signals starting in scanning mode. The radar emitter's response to the EW system's actions is determined by a pre-trained decision tree. It is worth noting that the simulator also allows the user to test different radar protocols. In this scenario, a mission failure is declared when the platform is within a radar's firing range and the radar is in fire mode for two clock cycles. To reduce simulation time, the simulator updates situations every 12 seconds of flight time. This clock cycle defines interval when the system updates the pilot's location and subsequently performs the EW analysis. Reducing this clock cycle results in finer location updates and more frequent EW analysis, thus being beneficial for generating more detail intensive simulations at the expense of increased calculations. Flight dynamics, Doppler Effect, and computational constraints were not investigated in this study. The purpose was to investigate ML's ability to decide optimal courses of actions to increase a pilot's survivability.

V. SIMULATION SETTING

A. SIMULATION PROCEDURE

Simulations begin with the initialization of the environment. The goal, mobile EW platform, and stationary radar locations are generated on a 2D grid. The emitter signal sets and PDW confidences are randomly generated for each radar location. The emitter modes are then determined based on the distance between the emitter and the platform. If the platform is within the radar's acquisition range, then the radar's mode is acquisition. If the platform is outside of this range, then the radar is in scanning mode.

At the beginning of each simulation cycle, the platform's location is updated. The platform is assumed to move directly towards the goal with a constant speed (482 km/h), unless the EW system's decision is to avoid a certain radar. The distance to each of the radar locations in the EW environment is then calculated. It is assumed that the EW system can detect a radar before the radar can detect the platform. This assumption is based on the fact that the radar's received signal undergoes round-trip path loss, while the EW system detects the radar signal with only one-way path loss. Although low-probability of intercept (LPI) radar is not considered in this study, the proposed EW system could be used to handle this case with modifications to the training data.

In this study, it was assumed that the EW receiver can detect a radar system at twice the distance of the radar system's acquisition range. It is also assumed that the system can obtain an accurate emitter location based on a sequence of angle of arrival (AoA) information. No additional investigation was done regarding the impact of the AoA accuracy. It is assumed that the AoAs were completely accurate, although it is understood that AoA calculations and subsequent range calculations are not necessarily trivial. Based on the system architecture, these inaccuracies will impact the calculated distances and the emitters might change states earlier than the system expects it to; however, no tests were conducted to measure these impacts, thus focusing on testing the proposed EW system architecture. The receiver errors considered in this study are misclassifying radar types and inaccurate knowledge about radar's working ranges in training data. If a threat radar has been detected, then the individual emitter threat level of the radar system is calculated using the Radar Threat Model. The threat level of the radar system(s) is then used by the EA decision tree, along with the radar's distance and operation mode in order to determine which action to perform. The EA Assessment Model can recommend (1) do nothing (2) avoid (3) apply EA and (4) apply EA to one radar and avoid another one. Once an action has been determined, the next radar state is predicted using the LSTM prediction model.

After an action has been performed by the mobile EW platform, even if it is to do nothing, the reaction of each of the radar systems in the environment is determined using the emitter reaction decision tree. The simulator then determines the platform's next location using the navigation method module and the simulation cycle continues until either the platform reaches the goal location, or it is intercepted by a radar's fire control mode within its firing range.

B. RADAR MODEL

There are 6 radar signal sets considered in this study. The EW system has countermeasures effective against radar sets 1-5; however, set 6 is unknown to the EW system. Therefore, the EW system has no effective countermeasure against signal set 6. The EW system can still detect its existence based on signal energy; nevertheless, it cannot determine its mode nor apply an effective EA against it. The reason for including unknown signals is to evaluate the performance of the EW system in the presence of an unknown radar.

The radars considered in this project can change their signal set if they are jammed. In each simulation, there are two separate radars, one of which can switch between signal sets 1, 3, and 5, while another radar can switch between sets 2 and 4, or between signal sets 2, 4, and 6. The first emitter set changes with the following pattern: $1\rightarrow3\rightarrow5\rightarrow1$, and the second set changes with the following pattern: $2\rightarrow4\rightarrow6\rightarrow2$. The unknown emitter (emitter 6) is triggered in specific simulations once the emitter set has been jammed consecutively through each of the prior emitters in the chain. The emitter types consist of different signal sets. The simulations only consider the two different transition sequences. Each emitter set changes types after being jammed for three cycles. The corresponding ranges of the different signal sets are shown in Table 2. Each of the radars are stationary with respect to the EW system.

TABLE 2. Emitter ranges.

Emitter Signal Sets	1	2	3	4	5	6
Acquisition Range (km)	300	400	500	300	300	450
Firing Range (km)	75	100	125	75	100	125

C. PDW CLASSIFICATION CONFIDENCE

An EW processing system is capable of classifying PDWs into radar types and modes. However, these systems will never be completely accurate due to imperfect received signals (e.g. low SNR, multipath, pulse-on-pulse interference). Therefore, the proposed EW processing system assumes that each of the PDW radar classifications have an associated confidence value. The proposed EW system is designed to engage at most two emitters, however it is provided three PDWs associated with three different emitters, where one of them is a false classification.

The EW processing system infers that the radar classification with the highest confidence is the actual radar type that is present. Each simulation is initialized to have an incorrect radar classification with the higher confidence value for one of the radar locations. This typically causes the EW processing system to make an incorrect decision for its first action. However, the system can learn when it has made an incorrect assumption about the radar type because it assumes that applying a correct EA will cause a radar system to transition back to scanning mode. Therefore, if the system applies an EA for a specific radar and it does not change to scanning mode, then the EW system identifies and corrects the false classification.

D. TESTED EW STRATEGIES

Five EW strategies, described below, are evaluated against the proposed EW system (referred to as "EW Sys" in Tables III-V), for a baseline comparison.

1) STRATEGY 1: DIRECTLY APPROACH GOAL

This is the most naïve approach for completing the mission. With this strategy, the platform proceeds directly towards the goal location and does not apply any EA or evasive maneuvers. This approach is gambling that the adversarial radars will not be able to respond fast enough to step through its modes and enter firing mode, which may be reasonable for fast or low observable platforms. Stealth technologies were not considered in this study.

2) STRATEGY 2: ONLY EVADING

In this approach, no effective EA can be applied toward an emitter. When the platform is within the acquisition range of an emitter, the system decides to evade the closest radar. This approach presumes that the platform can maneuver outside of an emitter's firing range prior to engagement, or that there exists a path between the starting and goal locations that is outside of radar coverage. Flight dynamics were not considered; however, this scenario creates a baseline for how difficult the EW environment is to maneuver without being detected. It ensures that there are no easy paths to the goal location.

3) STRATEGY 3: APPLY CONSTANT EA

This strategy has the EW system apply the same EA throughout the mission. The platform proceeds directly towards the goal location for this scenario. Once the EA decision tree determines to apply an EA, the system continuously applies this EA until the mission is complete. This is a naïve approach to engaging an adversary; however, it is reasonable if the radar's behavior does not change and the system has accurate information about the radar, which may have been the case in the early days of EW. PDW classification errors are not introduced for this strategy. This scenario is intended to illustrate why the system needs to adapt to the changing environment.

4) STRATEGY 4: CYCLE EAs

While applying this strategy, the platform proceeds directly towards the goal location and cycles through all possible EAs. The system applies a different EA during each clock cycle. Once the system has exhausted all options, it waits and applies no EA for one cycle and then restarts the cycle again. The system cycles through the EAs and there is no decision-making process. This is a reasonable approach to take when the EW system has no *a priori* knowledge about the radar emitters. This approach has the drawback of broadcasting the EW system's presence to other entities, with the possibility that no EA is effective against adversarial radars. This scenario is intended to illustrate the need for a "cognitive" element that is required to combat adaptive radar systems.

5) STRATEGY 5: EA DECISION TREE WITHOUT AVOIDING RADAR

In a scenario where there is a requirement for the platform to reach its goal location as quickly as possible, the actions are determined by the EA Assessment Model; however, the system ignores requests to avoid radar locations. This scenario is intended to determine the effectiveness of the EA decision tree.

VI. SIMULATION RESULTS AND DISCUSSIONS

A. SIMULATION PROCEDURE

Each of the cases were simulated 100 times and the number of successful missions was recorded. For each of the simulations, the goal location is first randomly assigned. The platform's starting location is next randomly assigned somewhere around the goal location. Finally, the radar emitters are randomly placed between the platform and the goal. The emitter locations are randomly offset from the exact center of the direct path. One of the emitters is intentionally misclassified at the beginning of tests for strategies 1, 2, 4, 5 and the proposed EW system. The emitter response decision tree model was used to model the emitters' responses to the platform's actions; therefore, an emitter's type changes throughout the simulation. There were two stationary emitters for each simulation and the goal for the pilot is to reach the goal location without having an emitter reach firing mode for two consecutive cycles.

B. VISULATION OF SIMULATION

The plot in Fig. 4 depicts a typical mission simulation. The green "v" is the platform's starting location, the green triangle is the goal location, the blue dots are the platform's path, and the stars are radar emitter locations. Within a certain distance of emitter location 0, the EW system recommended a change in trajectory to avoid a higher threat state. While the platform started in a location outside of the emitter's effective ranges, the system had already detected the emitters at the start of the mission because it was within twice the effective range of the emitters. Figure 4 illustrates a successful mission scenario. A successful mission is defined as a mission where a pilot reaches the goal location, and a failed mission is defined as a mission when an emitter is in firing mode for two consecutive EW system cycles.

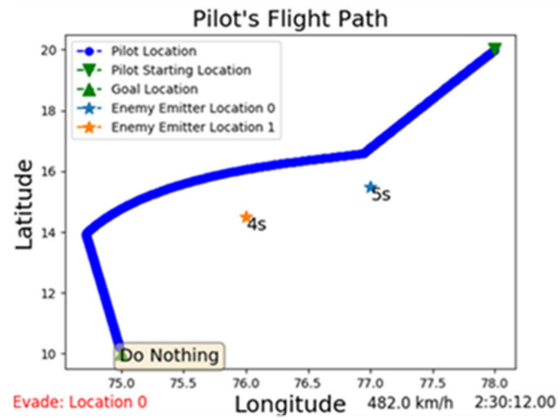

FIGURE 4. Example mission.

C. SIMULATION 1: NO UNKNOWN RADAR SIGNALS

In the first systematic simulation, every radar signal is known by the EW system and has a corresponding EA. The transition between radar signal sets is described in Section V. The results of the first simulation are depicted in Table 3. While simply evading the emitter and cycling through the possible EAs were rather successful, it is obvious that there is a significant benefit to include the decision-making process that was developed for the proposed EW processing system. The high success rate for scenario 2 signifies that there were not enough emitters present in the simulation. They were each placed offset from the middle of the pilot's starting location and the goal location; therefore, additional emitters offset further from the middle would likely decrease the success rate. Only two were simulated in order to maintain a reasonable simulation time.

TABLE 3. System simulation 1.

Strategy	1	2	3	4	5	EW Sys
Success Rate	2%	78%	5%	94%	100%	100%

D. SIMULATION 2: ONE UNKNOWN RADAR SIGNALS

In the second simulation, one radar signal set (set 6) is unknown to the EW system; therefore, there is no corresponding effective EA. The results are depicted in Table 4.

As shown in Table 4, when there is a radar system that the EW system does not have an effective countermeasure against, the best strategy is to avoid the radar system (strategy 2). Compared with the other strategies, the proposed

TABLE 4. System simulation 2.

Strategy	1	2	3	4	5	EW Sys
Success Rate	2%	78%	4%	4%	8%	38%

EW system has the best performance. Although the EW system directs the platform to avoid the unknown emitter, the emitter does not utilize the unknown signal set until it has been suppressed by EAs for a given number of cycles. In this case, the signal sets might change from 2 to 4 and then to 6. As the EW system has effective EA against signal sets 2 and 4, it has a false sense of security. However, once the radar changes to signal set 6, the platform might be too close to evade. In other words, the platform is deceived and trapped. This example demonstrates one of the challenges in decision optimization against agile, multifunction radar systems.

E. SIMULATION 3: ONE UNKNOWN RADAR SIGNAL AND CONSERVATIVE COUNTERMEASURES

A third simulation was conducted to evaluate the benefits of avoiding an unknown radar location (i.e. radar at location can transmit unknown signals) and applying more conservative countermeasures. Conservative countermeasures consist of applying a countermeasure a clock cycle later compared with the initial simulation, as well as avoiding the emitter that previously shot down a pilot. This simulation assumes that there is a posteriori knowledge of the unknown radar (with no effective EA countermeasures). Therefore, avoiding the discovered unknown radar system as early as possible ensures that the platform does not enter the radar's firing range. Applying more conservative countermeasures (i.e. applying countermeasures less frequently) conceals the presence of the platform from the radar for a longer period of time, which allows the platform to maneuver through the space without triggering the emitter to transition into the unknown signal set. The results of this simulation are depicted in Table 5.

TABLE 5. System simulation 3.

Strategy	1	2	3	4	5	EW Sys
Success Rate	2%	78%	4%	4%	32%	96%

It should be noted that there is a significant improvement in success rate by applying more conservative countermeasures and by avoiding the unknown radar location. This improvement arises purely from information gained from a previous mission failure, where the EW system was not able to counter the unknown radar. This is the driving factor for developing an LSTM neural network for radar signal predictions. If the model can predict an unknown signal in advance, then the EW system could implement a more conservative countermeasure scheme, which has been shown to increase the success rate.

F. LSTM STUDY

As shown in the simulation results, when there is an unknown radar signal for which the EW system does not have an effective countermeasure, a significant drop in success rate is observed. One possible way to improve the EW system's performance is to predict the radar's next move and take appropriate actions in earlier stages of the engagement. Therefore, if an LSTM model could accurately predict a radar's next signal, then this information might be useful for evading an unknown emitter earlier in the mission.

The LSTM is trained on a string of previous emitter types for a given location and it predicts the next emitter type. The training string grows with each simulation cycle as the previous detected emitter type is appended to the end of the training string. The LSTM is restrained as new information is obtained. If there were a previous mission in the area, then the model could be pretrained with previous observations; however, there is no way of knowing an adversaries' specific capabilities at a given location, therefore, this data needs to be collected in real-time. The structure of LSTM used in this project, as shown in Fig. 5, consists of three layers: input, LSTM, and dense. The input layer has 8 nodes which correspond to the length of sequence used to predict the next radar signal. The LSTM layer has 128 outputs and the softmax dense layer condenses the 128 inputs into 3 output values. The output of the dense layer signifies the confidence of the prediction for the three possible emitter types for the given location. The model is simple because the platform is assumed to have on-board capabilities for determining the emitter type; therefore, the LSTM is only learning a simple string of emitter types. Nevertheless, it is desirable to expand the functionality of the LSTM so it can be a part of an extended network to cover the complete range of variations observed in an EW environment and it will be a natural extension of this project.

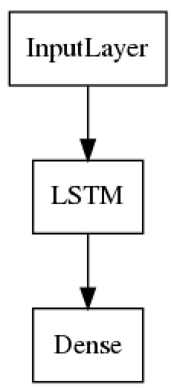

FIGURE 5. Developed LSTM.

The emitter predictions that the LSTM develops in the simulation are shown in Fig. 6. Figure 6 illustrates that, after a short transient period, the model can learn the pattern of how the emitter type changes for both radar locations. The orange line is the actual emitter type, and the blue line is the predicted

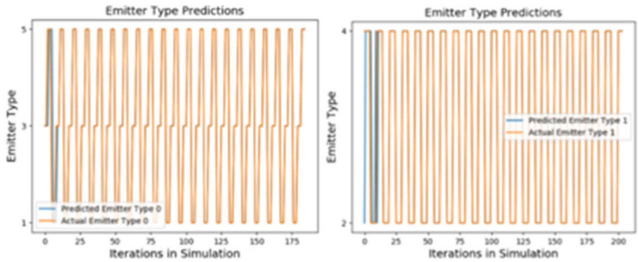

FIGURE 6. **Emitter type sequence prediction results.**

emitter type. The LSTM model was trained with a variable batch size that depends on the length of the training string; however, a fixed number of 15 training epochs were used for each retraining instance. The maximum string length for each batch was 8, which was long enough to capture the given emitter type change pattern. The loss function was categorical cross entropy. The model was then tested by providing the previous 8 observed emitter types for a given location and it estimates the next emitter type.

The results from this model could be used to verify the assumed emitter type that is present after initial training, and it could also be used to correct PDW classification error if necessary. It should be emphasized that, unlike the EA decision tree that is pre-trained before a mission, the emitter type prediction model is trained throughout the mission as information is discovered. The prediction performance converges rather quickly and overlaps the actual emitter type due to the emitter types changing in a deterministic manner as defined previously. Another cause for the fast convergence is the training string growing with each simulation cycle, which provides the model more information to learn from.

It should be mentioned that although initial PDW misclassification is taken into account, consecutive PDW misclassifications were not considered in this preliminary study of LSTM, which would likely worsen the LSTM's performance. For example, if there are consecutive PDW misclassifications, then the LSTM might misinterpret the ongoing emitter type pattern. It was assumed that onboard systems would recognize reoccurring PDW signatures and would better determine incoming PDWs, which would suppress consecutive misclassifications. An autoencoder layer would potentially improve the LSTM's immunity to PDW misclassifications if consecutive PDW misclassifications occur.

VII. CONCLUSION

EW environments are very difficult to analyze due to the large variability in data. EW systems need to be able to accurately model their environment to develop optimal decisions and maximize survivability. Therefore, a robust EW processing system that can propose optimal courses of actions is a pivotal piece of technology for modern systems.

The proposed EW processing system can analyze a varying EW environment and provide optimal sets of actions. Others could employ the developed system for their own operations by simply providing the necessary training data for the expected EW environment. This could greatly reduce the amount of time required to develop a custom EW processing system, as well as reduce possible human errors.

One possible item for future work would be updating the EA decision tree when new data is discovered. This would allow the model to optimize decisions in unknown scenarios that were originally not accounted for. This could be done naively by simply retraining the decision tree when new data is discovered, or by using online or adaptive decision trees. In the latter case, transfer learning would be very beneficial because a pre-trained system could be quickly updated with new information that might increase the pilot's survivability in blind situations.

Simulation results demonstrate that EW system's performance significantly suffers when there is a new threat. A well-developed LSTM model could predict the new threat, thus allowing the system additional time to evade the threat. Therefore, the integration of an LSTM model and the EW decision tree will be a logical extension of this project.

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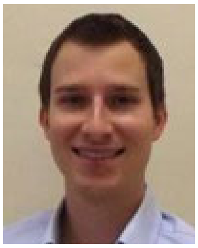

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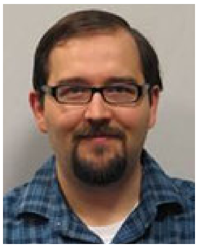

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