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REVIEW

Artificial Intelligence applications in Noise Radar Technology

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Abstract

Radar systems are a topic of great interest, especially due to their extensive range of applications and ability to operate in all weather conditions. Modern radars have high requirements such as its resolution, accuracy and robustness, depending on the application. Noise Radar Technology (NRT) has the upper hand when compared to conventional radar technology in several characteristics. Its robustness to jamming, low Mutual Interference and low probability of intercept are good examples of these advantages. However, its signal processing is more complex than that associated to a conventional radar. Artificial Intelligence (AI)-based signal processing is getting increasing attention from the research community. However, there is yet not much research on these methods for noise radar signal processing. The aim of the authors is to provide general information regarding the research performed on radar systems using AI and draw conclusions about the future of AI in noise radar. The authors introduce the use of AI-based algorithms for NRT and provide results for its use.

KEYWORDS

artificial intelligence, noise, radar signal processing, radar target recognition

1 | INTRODUCTION

Artificial Intelligence has been a topic with recurrent interest in a wide area of applications and radar technology is one of them. Designing waveforms with good properties using AI-based methods [1, 2] is an alternative to the classical deterministic radar waveforms and can provide good results when tailored for a specific environment or with a certain objective. In NRT, waveform design is an important barrier to overcome and these methods may prove a helpful tool in order to design a waveform with the desired characteristics as demonstrated in Section 3 (3.1). On the other hand, target classification is the topic were AI is being used the most in radar technology [3–6]. From the classification of human motion [4] to small drones [7] with radar scatter information such as micro-doppler information or range profiles is of high interest for a wide area of applications, such as military, navigation, home security and autonomous vehicle radar systems, just to name a few. In this paper, we will be addressing the research performed over the last few years in AI applied to radar systems and set guidelines to future research of AI-based methods in NRT with focus on its limitations. In the present section, NRT is introduced in Section 1.1 going through its definition, its differences to conventional radar, characteristics and advantages; in Section 1.2 AI is defined as well as its domains and reasons are given for its use in radar. Figure 1 summarises the fields of application where it makes sense to stand out for NRT and where it is believed that AI-based methods can be valuable and it will be the structure followed in this paper. The left side represents the optimisation of the signal before transmission whereas the right side refers to topics related to the received signal after transmission. Cognitive radar is the concept used for radars that continuously learn about the environment and adapt to it [8].

In ref. [9], an approach was made to define a layout for the use of Deep Learning (DL) in conventional radars. We propose a different framework to address the topics where AI will most likely have a significant impact in the future of noise radar systems.

Any wire or element connected to a Radio Frequency (RF) source radiates the signal and can be treated as an antenna [10].

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However, given that the antenna is resonant on the working frequency and matched to the RF source, the performance is very dependent on its shape [10]. Antenna design, which will be addressed in Section 2, refers to controlling currents in the transmitting elements in order to produce the desired radiation distribution [10]. The concept of antenna array dates back to 1906 [11] and it offers great flexibility for the radar system. This type of antennas has multiple elements organised on an array which is used to transmit the signal in a specific direction, rather than simply broadcasting in all directions. The elements of the antenna array are used to steer the direction of the combined transmitted signal by setting weights to the magnitude and phase of the transmitted signal in each element, and consequently contributing to a sum of all these signals, typically designated as antenna array beamforming [12]. Smart Antennas are a recent concept [13–16] that, based on antenna array beam optimisation is able to modify its pattern and adapt it to the operating environment conditions, resulting in optimised performance. Noise radar waveforms are of great use for phased arrays and Multiple-Input Multiple-Output (MIMO) configurations [17] since they have low crosscorrelation between them. This fact supports the use of MIMO configurations for NRT.

The antenna leakage problem is also addressed in Section 2 hence Continuous Wave (CW) radar systems such as noise radars, have a known limitation where the leakage from the transmitter to the receiver is present in undesired levels due to antenna coupling. This topic could be addressed in Section 4 since the used methods are usually applied to the receiver. However, for a simplicity purpose, and since there are also method which can be used before transmission, it was inserted in the section mentioned above.

Waveform optimisation methods are then discussed in Section 3. Waveform design is likely the most researched topic on this list when addressing NRT [18–22]. There are several performance metrics that are defined by the transmitted waveform. In ref. [23], a fundamental overview is done on radar waveforms, mentioning the main system performance metrics as SNR, range resolution, Doppler resolution, ambiguities in range and Doppler, range and Doppler sidelobes, and range-Doppler coupling. Section 3 discusses the main challenges for NRT waveform design, highlighting the ambiguities in range sidelobes caused by the statistical properties of the transmitted sequence as one of the most relevant limitations [19]. To address this problem, Signal-to-Interference plus Noise Ratio (SINR) and Integrated Sidelobe Level (ISL) are two of the most used design metrics and the foundation for the recent ones. SINR is most used as a metric for designing waveforms in communication systems, in MIMO [24] radars or any setting where minimising the interference is one of the objectives. On the other hand, ISL is a metric that expresses the goodness of the autocorrelation property of a sequence [25]. It evaluates the ratio between the energy of all sidelobes with respect to the energy of the main lobe [25], as in Equation (1).

$$\begin{aligned} \mathrm{ISL} &= \frac{\mathrm{SLS}}{\mathrm{MLS}} = \frac{\int_{-\infty}^{S_1} |r(\tau)|^2 d\tau + \int_{S_2}^{\infty} |r(\tau)|^2 d\tau}{\int_{S_1}^{S_2} |r(\tau)|^2 d\tau} \\ &= 10\log_{10} \sum_{k \epsilon SLS} |r_k|^2 (\mathrm{dB}) \end{aligned} \tag{1}$$

where SLS and MLS are the sidelobe interval and mainlobe interval respectively, $[S_1, S_2]$ is the interval containing the mainlobe and r stands for the output of the autocorrelation of the transmitted signal x, and r_k is the output of the autocorrelation of x_n in discrete time. Assuming the autocorrelation function is normalised, the mainlobe can be reduced to the sample where the lag is 0 and has a correlation value of 1. Therefore, ISL can be simplified to what is presented in Equation (1). Looking at the next topics, starting with waveform interception and recognition in Section 4, we enter a type of problem that can be typified as a classification one. It is important to distinguish between a few concepts, such as classification, recognition and identification. The process of identification following North Atlantic Treaty Organisation (NATO) AAP-6 Glossary of Terms and Definitions [26] is summarised in Figure 2.

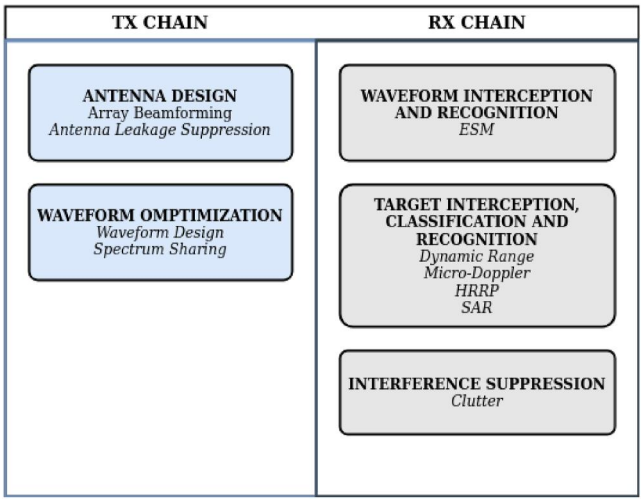


FIGURE 1 Areas where Artificial Intelligence (AI) is applied in radar.

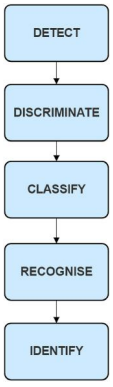


FIGURE 2 Process of identification following North Atlantic Treaty Organisation (NATO) AAP-6.

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As an illustrative example, let us now consider an F35 aircraft with serial number 1325 as the target of interest. The first step is to detect something from the environment, and then discriminate it. That is, in the presence of multiple-target, the ability to discriminate between all of them. The next step is to classify, that is, associate the target to a class which can be distinguished from others by at least one criteria—in this example, a fighter aircraft. Recognition is the ability to determine the nature of the target, discriminating an individual within a particular class—following the example, fighter aircraft F-35. Identification is the process of attaining an accurate characterisation of a detected entity so that high confidence real-time decisions can be made—fighter aircraft F-35 serial-number 1325 identified as foe. In ref. [27], more information is given on this topic.

The last step of this process may sound unrealistic in the current days; however, every target has different characteristics, even an aircraft or ship that were built on the same factory or shipyard have different radar cross sections and acoustic signatures. Adding on to these factors, with time wearing on, the targets are subjected to distinct conditions, and this creates differentiation between them [28].

In waveform interception and recognition topic, the objective may be to detect an incoming waveform from other system and recognise it to be able to use it for passive radar purposes or to associate the waveform with a type of transmitter and consequently, to a specific target—vehicle, missile, warship etc. Non-deterministic waveforms are harder to detect, and as a consequence research has been carried out in order to create new and better solutions to this issue, as it will be discussed in Section 4.

Automatic target classification is a topic with high interest, and is discussed in Section 5. Being able to know what type of target is detected gives a huge advantage. In military operations, the way weapons are employed depends on the targets capabilities—let us say the target is classified as a bomber aircraft: the manoeuvres and engagement will be different from a fighter aircraft. Other important application under this topic is automotive radar. Optical images have several limitations, such as night time and weather conditions, and that's where the radar can fit in very well. The detection and classification of targets in this conditions, specially for self-driving vehicles is important to give higher reliability to the system [29]. Several methods are being used to overcome this challenge:

- Micro-doppler information: targets make small movements such as vibration, rotation or tumbling that are specific to each one. A frequency plot along time—Time-Frequency Images (TFI)—can be used to classify the target [30–32];
- High Range Resolution Profile (HRRP): the magnitude of each range cell scattered on the target creates a specific plot depending on where the target is facing relatively to the transmitter—receiver. Ideally, all angles of the target are desired to train the algorithm and consequently get better results [33–39];
- Synthetic Aperture Radar (SAR) images can be used in several applications, usually for earth observations due to its capacity to provide images in any weather conditions and also at night time. This way, as in common optical images, targets can under certain conditions, be classified out of it [40].

In Section 6, clutter suppression is discussed. Clutter is the replicas of the transmitted signal echoed by undesired targets. It is an important topic for NRT since it's one of the main issues with these systems [41, 42]. Ground and sea clutter, being usually the strongest clutter, is the most researched for noise radar systems. The non-deterministic waveform causes a high range sidelobe level in the autocorrelation function as well as after the matched filtering caused by clutter, which can seriously affect the detection performance. The traditional way to tackle this problem is using Moving Target Indicator (MTI) filters. However, MTI filtering can only be applied to periodic signals, which is not the case of noise radars. The classification of a target in the presence of high levels of clutter is also a huge challenge as recent publications show [43].

1.1 | Noise radar technology

The working principle of a radar is simple in theory: transmit a signal in a certain direction and receive the corresponding echo, that is, an attenuated replica of the transmitted signal delayed in time and, depending on the target's velocity, deviated in frequency. By correlating the transmitted and received signal (matched filtering), the position and velocity of the illuminated target can be estimated. In conventional radars, the used waveform is deterministic [44]. Typically, Linear Frequency Modulation (LFM) is used due to its ease of implementation and low sidelobe level. Non-linear Frequency Modulation (NLFM) is also a common used waveform [45]. On the other hand, Noise Radar is a type of radar that transmits random signals, instead of deterministic ones. As a consequence of these characteristics, and in order to exploit the advantages of a NRT system, the transmitted waveform is continuous and Ultra Wide-band (UWB). This is, when the ratio of the signal's bandwidth to the centre frequency is greater than 25% [46]. This creates a demand for extremely high sampling frequencies for the Analogue-to- Digital Converter (ADC) and Digital-to-Analogue Converter (DAC), resulting in huge quantities of data to process [47]. ContinuousWave (CW) radars also present a challenge, which is antenna leakage due to coupling of the antennas.

However, the use of non-deterministic transmitted waveforms have several advantages [48] over the conventional ones:

- Low MI: When different radars coexist in a limited environment and frequency band, interference between them may occur. Since pseudorandom waveforms are realisations of a random process, two signals are theoretically uncorrelated with each other [49];
- Low Probability of Interception (LPI): The nature of the non-deterministic waveform provides more robustness against interception, and consequently, against identification and classification. Since the transmitted signal is random,

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there are no libraries from Electronic Support Measures (ESM) systems that contain them, and since they are treated as noise, it is harder to detect them in a low Signal to Noise Ratio (SNR) scenario, when compared with conventional signals. This topic is of high interest in military applications. There are already being developed methods intended to intercept this signals such as those based in spectral kurtosis [50] or AI [51–55];
- High Immunity to Jamming: Jamming, as referred in Section 6 can be used by creating deceptive false targets or injecting a signal to cancel the transmitted one, as well as other methods. These methods need information about the transmitted NRT waveform which is difficult to obtain since these signals are not periodic and the Fourier spectrum is equally distributed over the whole frequency band. In contrast to deterministic signals, periodicity with long observation times cannot be exploited.

Figure 3 gives a simple visualisation of a noise radar block diagram. Noise signal generation can be addressed digitally by applying optimisation algorithms such as polyphase sequences [56–58] or search algorithms [59, 60], which are discussed in Section 3 or it can be done the traditional way, by having a real noise source such as thermal noise and amplify it [48]. Lately, there has been some research using digital generation of noiselike waveforms with Field-Programmable Gate Arrays (FPGA). In ref. [61], a real-time digital signal generator based on a FPGA was proposed for different distributions. More approaches have been made, for continuous wave and pulsed noise radar [62–65]. Either way, waveform optimisation will be needed because NRT signals have a non-desired characteristic which is the fluctuations created on the autocorrelation function sidelobes. This is further discussed in III A. After optimisation is applied, the signal passes through Digital-to-Analogue Converter (DAC), is up-converted by using a mixer, amplified and transmitted. When the echo is received, the signal is amplified through the Low Noise Amplifier (LNA), down-converted using a mixer and passed through an Analogue-to-Digital Converter (ADC). The output of the matched filter will be the 2D-Cross Correlation between the transmitted noise signal and the received echo. These two dimensions are time represented by τ and frequency as doppler shift by υ in Equation (2).

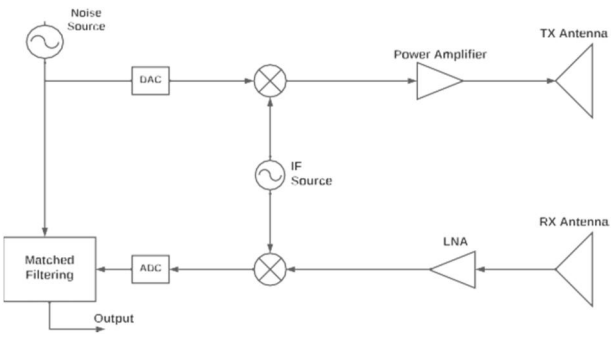


FIGURE 3 Simplified Noise Radar block diagram.

$$2\mathrm{D}-\mathrm{CCF}=\iint x(\tau)x_{\mathrm{rec}}(\tau-t)e^{2\pi j\upsilon t}d\tau d\upsilon \quad (2)$$

1.2 | Artificial intelligence

AI is the simulation of human intelligence processes by machines [66]. These algorithms are able to decide based on rationalisation done by them and achieve a certain goal. As stated in ref. [67], *AI will be such a program which in an arbitrary world will cope not worse than a human.*

AI is spreading in all fields of research and making great progress in many areas. In ref. [68], the role of AI is discussed in the near future and the impact it can have in different areas ranging from health care, marketing automation, aerospace and defence to financial risk management, cyber security and speech recognition. Good practical examples of how AI is directly impacting the way we do things is ChatGPT, DeepL Translate and DALL-E.

AI has many applications, from which we can distinguish the following:

- Machine Learning is the concept of having an algorithm which can make decisions, learn and adapt without human intervention. Like other sub-topics of AI, it can be used on a broad range of applications, such as radar technology [69] and Decentralised Finance (DeFi) [70];
- Computer Vision objective is to retrieve meaningful information from digital images or videos. It seeks to simulate human intelligence by creating automatic systems that can perform tasks similarly to the human eye and brain. In the radar field, SAR imaging is an important application, but this method is also being used for other tasks, such as real-time testing and visualisation of targets for automotive radar [71];
- Evolutionary Computation is a method used to solve complex optimisation problems using evolutionary algorithms inspired by natural evolution theory—natural selection. In radar, it has been used in the last 2 decades to design optimised waveforms for different types of radars and purposes [72] and less frequently used to other optimisation problems, such as antenna positioning [73];
- Neural Networks (NN) are likely the most researched topic in the recent years for radar applications [9]. It is considered a subtopic of machine learning but, in spite of that, is still a method used to radar applications that differs from the classic machine learning ones. Neural Networks try to mimic the human brain by using a variety of algorithms, performing a task by analysing training data and finding patterns that are highly correlated with a specific output. For radar applications, this method is being used to any of the areas presented before, such as human motion recognition in ref. [74] and waveform design in ref. [75].

Figure 4 represents the publications using the keywords Artificial Intelligence Radar on the past recent years (2015–2022) using IEEE Xplore database. This data provides a good overview on the growing interest of AI for radar applications.

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Table 1 presents several relevant and recent reviews on AI applied to the radar topics shown in Figure 1. It is easily understandable that target classification is the most researched topic using AI, whereas waveform design and recognition are less researched in conventional radars.

2 | ANTENNA DESIGN

First of all, it's important to differentiate phased array radars from MIMO ones, and to define what is intended by Antena Design. Phased array radars have been used for more than 5 decades. It uses an array of antenna elements where the relative phase of each signal coming through the element is varied in order to steer the radiated beam—**antenna beamforming**—this can be done with analogue beamforming (ABF) or digital beamforming (DBF). In contrast to MIMO radars, phased arrays are way simpler: the same waveform is transmitted over all the antenna elements and only the phase on the elements is changed to steer the beam. This creates a high correlation between elements that are distant on the array, that is, signal where the phase becomes similar. On the other hand, MIMO radars, are being used for 2 decades [83], and have a more complex approach: Instead of transmitting one waveform coherently, M orthogonal waveforms are transmitted simultaneously. From this, a virtual array can be created, because on each receiver element, M waveforms are received. Therefore, MN waveforms are processed, given N as the number or receiver antenna elements. As in ref. [83], diversity means superiority, and this offers better resolution, better sensitivity to the detection of lower speed moving targets, and several other benefits such as suppression of sea and ground clutter on certain type of radars [84]. An overview on the use of Machine Learning (ML) in MIMO radars can be found in ref. [85].

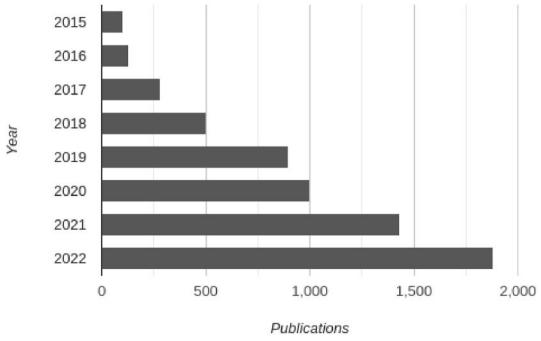


FIGURE 4 Publications on 'Artificial Intelligence Radar' in the last years using IEEE Xplore database.

2.1 | Array beamforming

By antenna design, we mean every effort that is being put into optimising an objective, for example, performance in a certain environment, by optimising the beam path radiated from the antenna whilst not changing the waveform before it reaches the transmitting elements. For conventional radar systems, AI-based methods have been used for array selection, optimisation of beam width and direction, achieving promising results [86–88]. A high interest application for radar technology is RF-based driver assistance systems for autonomous driving, mainly because, in contrast to detection through optical images, radar provides images and object detection in all weather conditions, especially during low visibility circumstances [86, 89].

Traditional radar systems antenna design issues, such as optimising radiation patterns and estimation of the antenna characteristics, is addressed in ref. [90], where an extensive review is done on AI-based methods for this purpose. Note that these problems are fundamentally the same for noise radar systems. Non-deterministic waveforms generated independently have already a low cross correlation. This fact poses already a decent advantage over conventional MIMO radars. On top of that, coding the noise waveform have been demonstrated do improve its orthogonality in ref. [91].

Noise MIMO radar dates back to the beginning of the century [92], and even tough it has several advantages, as already mentioned in this paper, there are also some

TABLE 1 Radar Artificial Intelligence (AI) recent relevant survey papers.

Radar application	Paper	References
General	Deep-learning for radar: A survey	[9]
	A comprehensive survey of machine learning applied to radar signal processing	[69]
Antenna design	A machine learning perspective on automotive radar direction of arrival estimation	[76]
Target interception, classification and recognition	Classification of SAR and PolSAR images using deep learning: a review	[77]
	A survey of deep learning-based human activity recognition in radar	[78]
	Application of deep learning on millimetre-wave radar signals: A review	[79]
	Artificial neural networks and deep learning techniques applied to radar target detection: A review	[80]
	A study on radar target detection based on deep neural networks	[81]
Interference suppression	Interference suppression using deep learning: Current approaches and open challenges	[82]

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disadvantages associated to the use of non-deterministic waveforms. Statistical variations in MIMO noise radar can impact the performance of the system [17] by degrading the beam patterns. Designing a set of orthogonal waveforms with desired characteristics attenuates this issue, as in ref. [93], a multi-cyclic algorithm original was proposed to design MIMO noise radar orthogonal waveforms. However, research in MIMO noise radar covers different issues. For target location estimation, antenna placement is analysed in ref. [94], an iterative conditional generalised likelihood ratio test is proposed to determine target's direction [95] and in ref. [91] a sparse reconstruction algorithm was proposed to estimate target parameters. Experimental results were obtained in ref. [96] for MIMO SAR Noise Radar.

AI-based methods can be valuable for optimising these waveforms by controlling the cross correlation between them, adapting to the scenario [97] or even optimise several other issues, such as the target location estimation problem.

2.2 | Antenna leakage suppression

Being Continuous Wave (CW) the desired geometry for noise radars, the leakage from the transmitter to the receiver is an unavoidable issue due to antenna coupling. One of the solutions, besides robust antenna components and careful antenna design, is to transmit a waveform with low autocorrelation sidelobes, which is something NRT is not particularly known for. Nevertheless, the tendency to mitigate this problem has been recreating the same signal with the leakage and subtracting it from the received signal in order to cancel it [98].

AI algorithms may be a valid choice to recreate the leakage signal efficiently, in order adapt to the environment and cancel it in real time. These methods may also help design arrangements or optimise components which minimise the leakage.

Even though these methods have not been used to address this specific issue, they are already being used to design antennas [99] and optimise waveforms (Section 3) and components [100], which validates the interest for future research.

3 | WAVEFORM OPTIMISATION

Designing a waveform to be transmitted can have several goals which are reflected on the objective function used. General waveform design is addressed in Section (3.1) as well as non-deterministic waveforms validation. Still in the present section, waveform design is addressed using an AI technique—Genetic Algorithms (GA). Lastly, spectrum sharing is discussed.

3.1 | Waveform design

A lot of effort has been put into optimising a waveform for radar applications, and there is a large amount of optimisation methods for sequences with low autocorrelation sidelobes, ranging from the design of polyphase sequences [56–58, 101] to the use of search algorithms [59, 60]. However, one of the biggest problems is the computational burden, leading to the development of new optimised algorithms capable of designing sequences with a large number of samples. Two of the most efficient algorithms are the Cyclic Algorithm New (CAN) [56] and Accelerated Monotonic Minimiser for Integrated Sidelobe Level (Accelerated-MISL) [57].

Several AI techniques can be used to design radar waveforms. It was shown in ref. [102] that neural networks can speedup autonomous radar waveform design up to 1000 times with low impact in performance when compared to traditional algorithms. In ref. [1] a new method for designing unimodular waveforms[1] with low autocorrelation properties was proposed based on CNNs using the average power level of autocorrelation sidelobes of the output phase as the loss function[2], providing better results than CAN and MISL algorithms. Variational Autoencoders (VAE) were also proposed in ref. [103] for waveform design by using a reconstruction loss method based on images of the ambiguity function to train the VAE. For MIMO waveform design in ref. [104], a feed-forward NN was proposed. GAs have also been used for waveform design since the beginning of the century [59, 105, 106] until recently in ref. [107]. The optimisation criteria typically used is related to the sidelobe level, such as ISL and Metric Factor (MF). However, the choice of Pulse Repetition Frequency (PRF) [59] in the case of pulsed radars and the choice of the energy levels on the Orthogonal Frequency Division Multiplexing (OFDM) [105] are also among the objectives of interest. One recent and promising approach for the use of genetic algorithms is multi-objective optimisation based on evolutionary algorithms such as NSGA-II. An algorithm can be developed and tailored to have low sidelobes at a certain range and have a Peak to Average Power Ratio (PAPR) close to 1. In this specific problem approach there are many optimal and local minima in different regions of the fitness landscape, so the use of crossover leads to a random search procedure, and this can be discouraging for the use of genetic algorithms [60]. RL is also being researched to radar waveform design [108], however results are way more promising for other topics, such as discussed in Section 6.

3.1.1 | NRT waveform design

Noise radar, although having numerous advantages as previously mentioned, makes a good example on the need to suppress the sidelobes of the autocorrelation function [109]. The random nature of noise signals leads to fluctuations of the autocorrelation function, resulting in randomness of range profiles. Putting this in to practice, lower sidelobe levels facilitate detection of weaker targets in the presence of noise or other targets. An extensive explanation is done for its

[1] Peak to Average Power Ratio (PAPR) has a value of 1.
[2] A loss function is a function that compares the desired and predicted output values; When training, we aim to minimise this loss between the predicted and target outputs.

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waveforms in refs. [19–21]. Also, in ref. [22], the trade-off between PAPR and random waveform LPI properties is addressed and quantified.

CAN-based algorithms have been applied in ref. [110] with good results and in ref. [19], a Filtering Method Algorithm (FMeth) is proposed to generate NRT CW waveforms with low sidelobe level and PAPR. However, there aren't yet AI-based methods being used for this specific topic, and following what was proposed in refs. [1, 2], this methods may have a great impact in the near future.

To begin with, when generating NRT waveforms, we need to understand that in order to exploit the advantages discussed earlier, the signal needs to be CW. This stands a challenge, since transmitting continuously a waveform brings hardware problems concerning the leakage between the transmitter and receiver antennas [19]. It also creates problems for waveform design, which we will address later in this section.

We've discussed how to generate pseudo-random waveforms in Section 1.1. In a simple way with PAPR = 1, a sequence $a = [e^{j\phi 1}, \ldots, e^{j\phi N}]$ is initially generated by randomly selecting values for ϕ given $\phi \in [-\pi, \pi]$, therefore maintaining the sequence unimodular. The autocorrelation of the transmitted signal x_n, r_k, is then computed in order to analyse the results and establish the metric to optimise. After that, there are several algorithms to optimise the transmitted signal as discussed earlier. This optimisation is needed for NRT because pseudo-random sequences present several challenges [19]:

- A non-deterministic sequence does not have a constant envelope; in fact, the sequence has an unpredictable envelope. Therefore, the PAPR, which is defined as $\frac{|x_{\text{peak}}|^2}{x_{\text{rms}}^2}$, giving that $\{x_n\}_{n=1}^{N}$ is the transmitted waveform, can be very high, which degrades the performance of the system;
- The fluctuations in the autocorrelation function discussed earlier are another challenge which depends approximately on the bandwith B and integration interval T [21]. The sidelobe level of the autocorrelation function can be estimated as PSLdB $= -10 \cdot \log10(\text{BT}) + \text{K}$ where K is a constant with values depending on the statistical properties of the pseudo-random sequence, usually in the range of $10 - 12$ dB [18].

From this, an important question may be raised: *how do we know that the sequence is random and therefore has the advantages of an NRT system?*

3.1.2 | NRT waveform validation

Not only in NRT, but also in applications such as cryptography [111], there is a need to obtain long pseudo-random sequences. In order to decide whether a sequence that is designed with the aid of AI-based methods for NRT purposes is non-deterministic and provides the advantages discussed, various statistical randomness tests need to be executed from a battery of tests that is usually used to define the quality of the design algorithm [112].

To begin with, we need to differentiate between the different types of random numbers: true random numbers, which are obtained by physical sources, for example, thermal noise; pseudo-random numbers, that are generated efficiently by computers, which require a seed, making them reproducible; quasi-random numbers, which are generated by specific algorithms having the points created evenly distributed to avoid cluster formations (low-discrepancy) [112]. For the NRT purpose, the interest is to generate pseudo-random sequences. [113].

Since the 1960's, random sequences are being evaluated by randomness tests [112]. *These tests are constructed as follows: Let us consider the null hypothesis H_0: Sequence designed by the algorithm is random.* Each test gives as its result a probability of rejecting this hypothesis given that is true—type I error.

There are hundreds of statistical tests, from cumulative and lagged sum to permutations, clustering and arithmetic mean, just to name a few. In ref. [112], a review on the most used batteries of tests is presented, and in ref. [114] recommendations are made for the use of the main test batteries. Table 2 summarises the main test batteries used for randomness tests.

These tests are supported on statistical hypothesis testing. These are defined as the null hypothesis H_0: *'The data sequence is random'* and H_1: *'The data sequence is non-random'*. When running each test, the randomness statistic is used to determine the acceptance of H_0, and therefore a p-value. It is essential to

TABLE 2 Main test batteries used for randomness tests, reviewed in [112].

Test batteries	Observations
Knuth [115]	It's the first test battery used for cryptography. Its use is currently set apart and other options are preferred for various reasons, such as its computational implementation and its facility to apply [114]. It includes 12 different statistical tests.
Dieharder [116]	This battery of tests derives from the Diehard one [117], introduced in 1995. There were some problems with this battery of tests: The test parameters are set by the software and cannot be modified like the allowed sample size which requires a binary file in the form of 32-bit integers [114]. Dieharder provides 26 different tests solving the problems stated for the Diehard test suite.
NIST [118]	Developed in 2001 by the United States (US) National Institute of Standards and Technology (NIST), NIST test battery was initially developed to detect non-randomness for cryptography applications and is currently widely used mainly for quality certifications.
TestU01 [119]	TestU01 was implemented in C and is easier to apply from a computational point of view when comparing to the main tests in the literature. The biggest drawback of TestU01 is that it can only run in C programming language.

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understand that we are not trying to prove that a sequence is random, but rather failing to show that is not random.

The computed metric, for this case, is the probability of having a sequence that is *more random* than the perfect random sequence which is defined by each specific test. To accept the null hypothesis, a significance level, α, is defined and therefore, we can say that H_0 is accepted if p-value $\geq \alpha$, where $\alpha \in [0.001, 0.01]$.

3.1.3 | NRT waveform design with genetic algorithms

GA is a subset of Evolutionary Algorithms (EA), which was already presented in Section 1. These algorithms are an approach to solving problems in a similar way to natural selection. EA usually contain a first step of initialisation, a second one of selection followed by a loop process of genetic operators driven by the crossover and mutation operations, and finally by a termination step [120].

Once a population is initialised, the portion with the top fitness score, according to a fitness function, is selected. In the case of multi-objective optimisation, instead of a single solution, there is a set of optimal solutions denominated the Pareto set. After this selection, these members are used to create a new generation with the use of crossover, which uses the characteristics of the selected parents to create new children for the new generation, maintaining the genetic material, and with the use of the mutation operation, which introduces new genetic material. This process is finished with a stop condition such as maximum number of generations or reaching a performance termination criteria.

An example of a Single Objective Optimisation (SOO) GA algorithm is to minimise ISL as the objective function, having a Gaussian distributed noise signal as an initial signal to modulate. For illustration purposes, let us consider a signal with 2048 samples and that is put through 100 generations. By generating the phase ϕ and computing the complex sequence, the signal is unimodular, that is, PAPR = 1 and the criteria $|x_n| = 1, n = 1, \ldots, N$ is verified. Therefore, the optimisation problem can be expressed as follows:

$$\begin{cases} \text{minimize ISL} = \sum_{k=1}^{N-1} |r_k|^2 \\ \text{subject to } |x_n| = 1, n = 1, \ldots, N \end{cases} \quad (3)$$

Multi-Objective Optimisation (MOO) using genetic algorithms might be of interest for NRT by setting as objective functions ISL and PAPR. Having a high PAPR degrades the system performance and it is crucial to minimise this metric or setting it to 1—unimodal sequence. In the MOO case, the generated sequence won't be unimodular, but the tradeoff between the gained PAPR to the lowering of the sidelobes can be advantageous. Having PAPR and ISL as objective functions or constraints for an algorithm is not a new idea. It has been proposed in several recent papers [121–123] for MIMO radar waveform design applications. The MOO problem presented is expressed as:

$$\begin{cases} \text{minimize ISL} = \sum_{k=1}^{N-1} |r_k|^2 \\ \text{minimize PAPR} = \dfrac{|x_{\text{peak}}|^2}{x_{\text{rms}}^2} \end{cases} \quad (4)$$

For MOO problems, solutions do not usually converge to a single point. Instead, we have a set of optimal solutions—Pareto set—which are also called non-inferior, admissible, or efficient solutions [124]. The non-dominated vectors, when plotted in objective space, are known as the Pareto Front (PF).

3.2 | Spectrum sharing

The last subtopic in waveform optimisation is minimisation of the interference from other signals. As the spectrum gets more crowded, conventional radars need to adapt its waveforms to operate in this conditions. In ref. [125], ML methods have been introduced to spectrum sensing. In ref. [126], RL was used for the radar to avoid batches containing interference signals. The authors compared the state-of-the art spectrum sharing methods for radar with RL ones, and concluded that the use of RL results in a decrease of MI. RL has shown good results on this application field [108, 127]. However, since the nature of random waveforms provide robustness against interference, the application of AI-based methods to spectrum sharing in noise radar may not be a priority. In ref. [128], it was shown that pseudo-random sequences modulated in a transmitted waveform have high robustness to interference, showing a maximum of 1.5% detection error on a controlled environment with a detection range of 10 m; in ref. [129] the interference in conventional magnetron marine radars was investigated and an approach to marine noise radars was proposed to mitigate mutual interference.

4 | WAVEFORM INTERCEPTION AND RECOGNITION

The following sections address the optimisation of the signal after transmission, as illustrated in Figure 1, on the right hand side.

In particular, this section addresses the AI-based optimisation techniques in order to intercept and recognise a waveform more efficiently.

4.1 | Electronic Support Measures

Two-channel CNN with bi-directional Long Short- Term Memory (LSTM) was used in ref. [130] to recognise passive radar waveforms from an illuminator of opportunity. It

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achieved good performance when comparing to other state-of-the-art methods and introducing transfer learning to the waveform recognition model transferability problem, lowering 60% on training time and 50% on training data compared with training from scratch. Transfer learning methods were also used for waveform recognition purposes, usually by using 2D TFI [30–32] which are created by the Choi-Williams distribution method. CNN-based methods have shown to have superior performance in refs. [51–55] using mostly Time-Frequency Analysis (TFA) techniques.

In ref. [50], an approach is made to detecting a marine noise radar signal by using a spectral kurtosis method achieving detection with lower SNR. Even not having AI-based methods for noise radar waveform recognition yet, it is important to understand that not every task is optimally solved by applying some sort of AI algorithms. Like in ref. [50], the same tasks can be more efficiently achieved by applying some simpler methods. In NRT, ideally its waveforms are never the same or the database that contains is very large. This can lead to future research in transfer learning methods in order to have a smaller database as it was proposed in ref. [130]. With the rising interest of research in NRT, AI-based methods might appear applied to noise radar waveform recognition. However, other most effective methods might be the only contenders in the near future, as in ref. [50].

5 | TARGET DETECTION AND RECOGNITION

For NRT systems, remembering it is an UWB radar, it can stimulate more target's resonance regions of the scattering spectrum and therefore, obtaining more information that is fundamental to the detection and recognition process. Several DL-based methods are being proposed to make use of UWB systems for target recognition, such as in ref. [131] for hand-gesture recognition. Even though this allows more flexibility to the system detection and recognition process, real-time digital signal processing is still very complex. It is also important to mention, that the sections addressing Micro-Doppler and HRRP are not of special interest for noise radar systems alone, but because of the high focus on research of this topics with AI-based methods and being NRT systems UWB, it makes sense to include them for the sake of giving recent research and valuable information to the reader, which can translate to future NRT applications.

Noise radar detection faces different challenges when comparing to the conventional radar. The main barrier for conventional radar detection is to design a system robust enough to interference without knowing its shape. However, in the case of NRT, the detection is relatively simple and robust to external interference, as shown in ref. [132]. Nonetheless, these systems major drawback in the detection process is the limited dynamic range caused by the fluctuations of the correlation function.

In AI, DL is getting a lot of attention, and even though it can provide the ability to find patterns and achieve more accurate results than the simpler and mostly linear methods, radar captures huge amounts of data from the environment that it is scanning. This being said, it is understandable that the feature space gets very complex and non-linear, leading to the main challenge of Automatic Target Recognition (ATR): the limited dataset for training the classification algorithms. DL requires a huge amount of data, especially when we are talking about sensors [133]. We need to have a sufficiently critical understanding to recognise that we are addressing very complex problems in a small controlled environment—for example, there is a huge difference in classifying human activity when there is a radar that is specifically designed for it and the data is easily obtained to training purposes from trying to recognise a combat vehicle 10 km away when the data for training purposes is classified and hard to obtain; the scattering signal has different characteristics specific to its radar, from a certain angle; the Radar Cross Section (RCS) is different to every vehicle.

There are already some datasets that are frequently used such as the Defence Agency Research Project Agency (DARPA) Moving and Stationary Target Acquisition Recognition Dataset (MSTAR) [134] for SAR, including radar images from two different depression angles for 10 different targets.

5.1 | Dynamic range

The dynamic range of a radar system enables to detect targets with low reflectivity while detecting strong echoes without overloading. In a simpler way, it is the relation between the highest and lowest detectable signals. The high sampling rate demand of the ADC which digitises the noise signal, leads to smaller depth. The depth, or number of bits of the ADC, determines the relation between the smallest and highest observable signals, or in other words, the dynamic range. Several techniques are being used to mitigate this problem. Adaptive filtering was proposed to address this problem in ref. [132], whereas in ref. [135], a stepped-delayed method was used. The design of such radar systems is based on analogue processing and digitising the results at a lower frequency, which limits the flexibility of the radar system.

Other techniques were proposed to detect man-made targets with the presented limitation. The fact that numerous man-made targets can be modelled as the sum of a few predominant scatters, is something we can take advantage of ref. [47]. In ref. [136], it was proposed modifying the emitted waveform by summing delays of the original signal with the objective of matching it to the scattering centres. This creates an enhancement of the correlation function and provides better detection. Yet, the drawback of this method, is that the waveform is tailored only for that specific target and will not be useful for other scatters. Based on this method, the authors in ref. [137] presented transmitting the original noise waveform without any modification. The summed waveforms to match the target's scatter centres is instead, the reference signal, which will only be used as reference for correlation for the target area, allowing then the use of the transmitted waveform for other purposes.

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Even tough AI methods haven't been used for NRT purposes, a DL-powered ADC was proposed in ref. [138] for wideband signal receivers, which can translate to research on noise radar systems.

5.2 | Micro-Doppler

Micro-Doppler information from targets is valuable and can be a relevant feature. Before the classification process, TFIs are created and then the problem can be addressed as an image classification one. Traditional ML methods have been used for this application: SVM in refs. [139, 140], Maximum a Posteriori (MAP) in ref. [3], decision trees in ref. [141] among others. On the other hand, DL-based methods bring certain advantages as automatic feature extraction and classification boundaries saving time and committing fewer errors [142]. CNN have been used to accurately classify drones and birds [143] concluding that, as already mentioned, the larger dataset implies better performance. CNN have been also used to classify human motion in refs. [4–6], ornithopters in ref. [144], and small drones in ref. [7]. Recurrent Neural Networks (RNNs) were also used for drones and bird classification in refs. [145, 146], human motion in refs. [147–149] and for different targets in [150] resulting in good accuracy but high computational load. The main reason for the performance obtained is claimed to be the ability of RNN models to analyse temporal dependence of the micro-Doppler signatures [150] being LSTM is the method in RNN mostly used. Convolution Autoenconder (CAE) were also used in ref. [151] to recognise human activity showing better results than the other proposed methods, but higher computational complexity.

Genetic algorithms have also been used in ref. [152] to estimate parameter of a micro-Doppler parametric model for space targets scattering centre estimation, and in ref. [153] to extract the micro-Doppler effects instead of using TFIs. In ref. [154], a genetic algorithm back-propagation method was used in NN to classify ground targets from an Unmanned Air Vehicle (UAV). An extensive and recent survey on micro-Doppler target classification and recognition is presented in ref. [155].

Noise radar systems provide better performance when recognising tasks since the system is UWB. The rapid cost reduction of systems that can produce reliable micro-Doppler information such as noise radar, provide the essential tools for near-future research in micro- Doppler techniques. [156] demonstrated that these systems allied with AI-based methods can improve significantly the recognition task. [157] also concluded that UWB radar adds an extra degree of freedom to micro-doppler information, increasing the features that may be observed, therefore improving its performance. The radar system performance can always be enhanced, however, the successful solving of the mapping between signatures and the real targets can definitely improve the performance of the classification and recognition. Future research on this topic should focus on postprocessing the information collected such as classification and noise removal algorithms [158].

5.3 | High-resolution range profile

A lot of research is being put into using HRRP of targets. Back-propagation methods based on genetic algorithms were also used for neural networks using HRRP. RNNs have been used in ref. [34] to hand gesture recognition achieving 99% accuracy in 10 different gestures, in ref. [35] for 6 different activities in human activity and in ref. [36] RNN with Gaussian mixture model demonstrated good robustness against HRRP shifts. CNNs methods were proposed in ref. [37] to distinguish between 3 aircraft, in ref. [38] to do a study between traditional ML algorithms and CNNs and in ref. [39] to recognise ground targets. In ref. [159], CNNs and bidirectional RNN were applied to target recognition making a step towards having smaller training datasets and achieving similar performance. CNN were also used with bidirectional Gated Recurrent Unit (GRU) achieving a recognition rate over 93% for 30 dB SNR and outperforming some state-of-the-art ML and DL methods.

With these last two topics, we can see a preference of classification algorithms for DL methods. In ref. [133], an AI/Automatic Target Recognition (ATR) hierarchy chart is presented for when to use certain methods and what for, which is summarised in Figure 5.

Authors highlight that the presentation of results—classification/recognition task—should build up decision making and not be the autonomous machine decision maker. DL alone won't make improvements, but dividing the ATR process will.

5.4 | Synthetic Aperture Radar

Carl Wiley invented the first SAR back to 1951 [160]. Since then, SAR technology had a huge evolution and is now of extreme importance in both civil and military domains. The main advantages are that SAR can collect high-resolution images in any weather conditions, flight altitudes independently

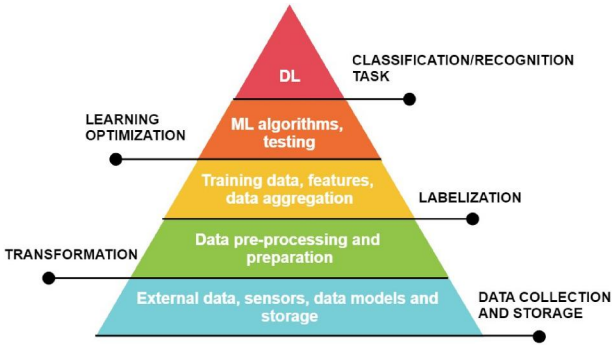


FIGURE 5 Artificial Intelligence (AI)/Automatic Target Recognition (ATR) hierarchy chart based on [133].

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of weather and daytime [160]. The applications are easy to name when these advantages are mentioned. Military surveillance, topography and monitoring of volcanoes, earthquakes and crop growing [161, 162] are just a few.

A review on the use of DL techniques for SAR is presented in ref. [77] identifying CNNs as the most used method over SAR target classification and identifying future scopes of research in this field. Optimisation tasks, such as SVM parameter optimisation are proposed in ref. [163] using a variation of genetic algorithm—improved Harris's Hawk Optimisation (HHO). In refs. [164, 165], genetic algorithms were used in SAR ATR modelling.

In ref. [166], a deep forest model was proposed to classify 10 different targets from MSTAR dataset. Still using the same dataset, in [167] authors explored the usage of other information from SAR besides images, such as phase information. A high number of papers were published using variations of CNNs [168–174].

LSTM-based methods achieved good results in using less data for training, while maintaining accuracy. In refs. [175] and [176], the problem of having very limited datasets was addressed by using transfer learning from optical images. The authors concluded that a deep network pre-trained with a large-scale annotated SAR scene dataset is a good source to apply transfer learning. They also discouraged the use of optical images pre-trained model straightforward to SAR, proposing a Multi-Kernel Maximum Mean Discrepancy (MK-MMD) based transfer method in order to improve performance.

Experimental results were obtained in ref. [177] using compact CAEs outperforming the existing DL-based methods for the case of small training samples. Autoencoders were also used in ref. [178] under SVM and K-Nearest Neighbours (KNN) achieving high accuracy.

SAR imaging using Noise Radar is investigated in ref. [179] demonstrating that NRT may provide high performance for some application such as airborne and spaceborne SAR because of its waveform properties and for short-range applications in ground-based SAR. NRT offers significantly low transmitted power and an affordable system while still achieving fast data acquisition and good electromagnetic compatibility. In addition, UWB radars such as noise radar systems, greatly improve ground range resolution of SAR systems, which can be verified by the Equation (5), with η as the incident angle, B the bandwidth and c the speed of light.

$$R = \frac{c}{2B\sin\eta} \tag{5}$$

6 | INTERFERENCE SUPPRESSION

There are several ways a radar can suffer from interference. From phase difference in different receiving channels [180] and MI to jamming and clutter/multipath. In this section, the application of AI to clutter suppression is presented as well as considerations for NRT.

6.1 | Clutter

Clutter originates from several different sources, such as point-clutter that includes radar signal returns from objects such as a house, or an animal, to weather, ground and sea clutter. Each type has its own characteristics and produces different returns that can be classified.

Sea clutter stands as a high barrier for marine radars. ML algorithms—SVM and KNN—have been used in ref. [181] to classify whether a return is clutter or a target. In ref. [182], a deep neural network having two Generative Adversarial Network (GAN) has been efficiently employed to sea clutter suppression. This method also accounts for the preservation of target information. GAN-based algorithms have also been used for the same purpose in ref. [183] and CNNs have been efficiently used in ref. [184]. Clutter has a big impact on CW UWB systems. Antenna leakage and strong echoes, originated from ground or sea clutter can completely mask the weak target return. A detailed discussion for multipath and clutter in UWB CW noise radar systems is presented in ref. [185] with real data analysis.

Over the past few years, several techniques have been used to mitigate this issue in NRT: In ref. [186] and adaptive sea clutter canceller was used to suppress clutter returns, whereas in ref. [187], a modified Extensive Cancelation Algorithm (ECA) was proposed for clutter suppression on moving platforms. In refs. [132] and [188], a waveform design approach was proposed to suppress clutter with very low computational cost comparing to the previous methods.

The authors in refs. [41, 43] present an insight on ground clutter returns and its impact on NRT, proposing non-AI-based methods for its suppression, such as unmatched filters. Clutter suppression might be a field, similar to waveform optimisation, where AI-based methods may achieve promising results, such as in conventional radar systems.

7 | FINAL CONSIDERATIONS

This paper's objective was to provide general information regarding the research performed on radar systems using AI and draw conclusions about its future in NRT. It also introduced the basic tools to, not only understand how novel AI-based methods can be applied to radar technology, but also to show that it can be efficiently used for NRT and, most importantly, give a guidelines and comparison values to future research in this topic.

To achieve the proposed objective, the review followed the organisation presented in Figure 1. On each topic proposed, a review of the research with the most impact is done followed by notes on the application of these methods to noise radar. In Section 3, the most relevant for NRT, a simulation of an approach to MOO is presented for future research in NRT waveform design. A correlation between the application of AI different areas to the different topics in conventional radar and NRT was also made along the paper.

Noise radar has as one of its main obstacles the high level of its autocorrelation sidelobes [109], and AI-based methods

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have been utilised more frequently to design sequences with properties such as low autocorrelation function sidelobes using objective functions such as ISL—Section 3. However, to develop these sequences and to take advantages of NRT properties we have to make sure that this signal is non-deterministic. This problem was addressed in Section 3 (3.2).

Dynamic range and antenna leakage are also very limiting issues for NRT, which are addressed in Sections 2.2, 5.1 and 6.1.

NRT is still a developing technology, although it has already been successfully applied in various contexts [109, 189]. On the other hand, AI is being applied in a lot of fields, and Figure 4 sums up really well how AI can be impactful in radar. This paper leaves a general theoretical framework basis and a practical foundation for future research in NRT waveform design, using genetic algorithms and also going through the validation of noise waveforms.

AUTHOR CONTRIBUTIONS

Afonso L. Sénica: Conceptualisation; formal analysis; investigation; methodology; software; visualisation; writing – original draft. **Paulo A. C. Marques:** Formal analysis; supervision; validation; writing – review and editing. **Mário A. T. Figueiredo:** Supervision; validation; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors certify that they have NO affiliations with or involvement in any organisation or entity in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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