A Deep Learning Application for Dolph-Tschebyscheff Antenna Array Optimisation

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***Abstract*—This paper proposes a design for a Dolph-Tschebyscheff-weighted microstrip antenna array using a deep learning application. For this purpose, a multilayer perceptron and a deep learning model, both created using the same data set generated by a genetic algorithm, were compared. The antenna array population is initially generated randomly and then optimised with a genetic algorithm. The data produced by this model becomes a data set used for training in the deep learning application. The dimensions and specifications of the antenna array are obtained from this application, ensuring precision and optimisation in the design process. A new microstrip antenna array structure is employed for the proposed method, taking advantage of this design technique. The Dolph-Tschebyscheff weights are applied to achieve better characteristics for the microstrip antenna array, thus obtaining low side lobe levels, which are crucial for enhancing signal clarity and reducing interference. The results demonstrate that the proposed algorithm significantly improves the specifications of the structure. This improvement highlights the potential for integrating deep learning with traditional optimisation algorithms for advanced antenna design.**

***Index Terms*—Antenna modelling; Dolph-Tschebyscheff; Deep learning; Genetic algorithm.**

I. INTRODUCTION

The need for higher data capacity in wireless communication has been increasing day by day. Antenna arrays are key elements in modern communication systems and offer the ability to direct radio frequency energy in specific directions with high efficiency. With the great increase in available wireless devices, new techniques seek to design them for several requirements. For these requirements, novel techniques and novel integrated algorithm models are available for designing antennas. Design and optimisation of antenna arrays are critical to achieve desired radiation patterns and to improve the performance of communication systems. Genetic algorithms (GA), deep learning (DL), and the Dolph-Tschebyscheff distribution are widely used in antenna design. However, the integration of these methods with modern deep learning techniques can further improve the radiation pattern optimisation process. This paper presents a novel approach where GA outputs are used as input to a deep learning model and is further refined with the Dolph-Tschebyscheff distribution.

Microstrip antennas are widely used in many practical applications, such as in aircraft and satellite communication systems and radars. This structure has many well-known advantages, such as low profile and lightweight design [1]. To run a wireless communication system at its most efficient level, antenna optimisation, design, and selection are crucial [2]. Most antenna modelling studies include a number of computer-based models, such as GA, DL, and multilayer perceptron (MLP) [3]. When an antenna is not well optimised, it cannot emit in the manner it was intended for. To improve the overall performance of the antenna and save time in the layout design process, researchers are increasingly using DL techniques [4]. The quality, quantity, and accessibility of the data are critical to the success of DL systems. From the standpoint of antenna design, these data must be gathered, because currently there are not enough standard antenna data sets [2].

Although series fed antenna arrays solve the power loss problem with good efficiency, the side lobe level (SLL) in a uniform current distribution case is high [5]. On the other hand, high SLL causes false target detection in radar operations, data errors in communications, and military applications [5]. The optimal beamwidth for a specific SLL is provided by the Dolph-Tschebyscheff antenna array method, which obtains weights for uniformly spaced linear arrays [6]. As a result, some of the strategies that reduce the SLLs of the antenna radiation patterns are investigated in this study.

In electromagnetism (EM) optimisation problems, GA is one of the first evolutionary algorithms to be used [7]. GA has critical mechanisms such as selection, crossover, and mutation and takes advantage of these [8]. In the selection mechanism, individuals are chosen that are suitable for the fitness function. The fitness function confirms the performance of the antenna array. Crossover creates new individuals from existing population by changing some parts of the chromosomes. Mutation allows the creation of a new individual from an existing individual by randomly mutating one or more characteristics for a chosen individual. This process has been continued until the finishing criteria of the

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algorithm are satisfied. Finishing criteria is the number of iterations of the GA in the proposed model. The specifications of the antenna array are transformed into a chromosome. And all these GA mechanisms are applied to these chromosomes.

The use of design models using DL in antenna modelling, analysis, design, and array radiation synthesis is increasing rapidly [9]–[13]. These models improve engineering processes by offering higher accuracy and efficiency compared to traditional methods. In addition, DL-based approaches have the ability to optimise complex antenna structures and make performance predictions faster and more accurately.

Previous studies have shown that Dolph-Tschebyscheff weighted antenna arrays offer advantages in various applications. For example, the effectiveness of genetic algorithms in antenna array optimisation has been investigated, and their results have been shown to provide important improvements in radiation patterns [14]. Similarly, the use of deep learning techniques in antenna design has been studied, and these methods have been shown to provide faster and more effective results than traditional optimisation techniques [2]. In addition, significant gains have been achieved by using artificial neural networks to improve the performance of microstrip antenna arrays has [15]. The main concept of the DL algorithm is to learn behaviours in the data [16], which makes it useful in many disciplines [17]. In this study, the DL and GA methods have been used with the aim of achieving low SLLs.

II. MICROSTRIP ANTENNA ARRAY STRUCTURE

In spacecraft, aircraft, satellite, missile, and any other high-performance applications, where weight, size, cost, ease of installation, performance, and aerodynamic profile are constraints, low-profile antennas may be required [1]. To meet these requirements, occupy less space, increase bandwidth, and microstrip antennas can be used [1].

In this study, the shape of the microstrip antenna is a rectangular patch given in Fig. 1 [1].

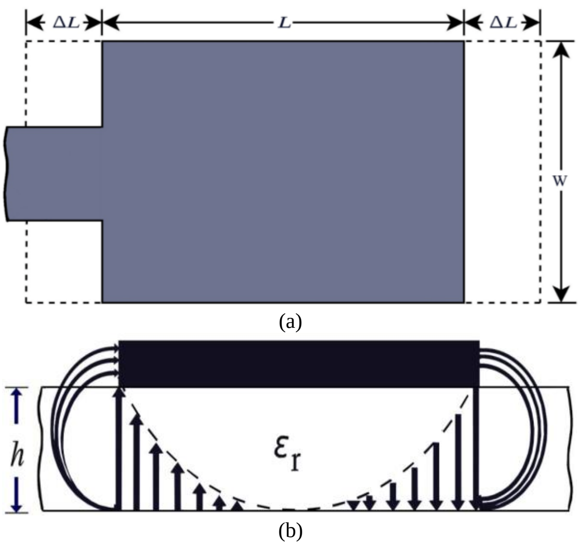

Fig. 1. Physical and effective lengths of rectangular microstrip patch [1]: (a) Top view; (b) Side view.

Equations (1) to (5) are used to calculate the effective patch length, the patch length, the effective dielectric constant, and the patch width [1]. The notation and descriptions used are given in Table I.

TABLE I. NOTATIONS USED AND DESCRIPTIONS.

Symbol	Description
v_0	The free-space velocity of light
f_r	Resonant frequency
h	Height of the substrate
ε_r	Dielectric constant of the substrate
ε_{reff}	Effective dielectric constant
λ	Wavelength
W	Width of the antenna
L	Length of the antenna
d	Spacing between the elements

Equation (1) is used to calculate of the length of the antenna

$$\Delta L = 0.412h\frac{\left(\varepsilon_{reff}+0.3\right)\left(\frac{W}{h}+0.264\right)}{\left(\varepsilon_{reff}-0.258\right)\left(\frac{W}{h}+0.8\right)}. \tag{1}$$

As given in Fig. 1, the length of the antenna has been extended by ΔL for each side. To avoid the fringing effect, (2) is used for calculations of the length of the patch antenna

$$L_{eff} = L + 2\Delta L. \tag{2}$$

The actual length of the microstrip antenna is determined by (3), where the permeability constant is μ_0 and dielectric constant of the free space is ε_0

$$L = \frac{1}{2f_r\sqrt{\varepsilon_{reff}}\sqrt{\mu_0\varepsilon_0}} - 2\Delta L. \tag{3}$$

The effective dielectric constant changes with frequency and (4) gives this formula. For the case where the width is greater than the height, the equation becomes the following

$$\varepsilon_{reff} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left(\frac{1}{\sqrt{1+12\frac{h}{W}}}\right). \tag{4}$$

The width of the patch is given in (5)

$$W = \frac{v_0}{2f_r}\sqrt{\frac{2}{\varepsilon_r+1}}. \tag{5}$$

These microstrip patch antenna's equations are implemented to optimise the microstrip patch antenna structure in GA and DL.

III. DOLPH-TSCHEBYSCHEFF DISTRIBUTION

To achieve better beamforming, the smallest side lobes are required. A linear array with uniform spacing, non-uniform amplitude is a solution for this.

The popular distribution method is Dolph-Tschebyscheff whose excitation coefficients are coming from Tschebyscheff polynomials which are given in Table II with the identity equation (6)

$$u = \frac{\pi d}{\lambda}\cos\theta. \quad (6)$$

TABLE II. EXCITATION COEFFICIENTS USED.

m	**cos(*mu*)**
0	1
1	$\cos u$
2	$\cos(2u) = 2\cos^2 u - 1$
3	$\cos(3u) = 4\cos^3 u - 3\cos u$
4	$\cos(4u) = 8\cos^4 u - 8\cos^2 u + 1$
5	$\cos(5u) = 16\cos^5 u - 20\cos^3 u + 5\cos u$
6	$\cos(6u) = 32\cos^6 u - 48\cos^4 u + 18\cos^2 u - 1$
7	$\cos(7u) = 64\cos^7 u - 112\cos^5 u + 56\cos^3 u - 7\cos u$
8	$\cos(8u) = 128\cos^9 u - 256\cos^6 u + 160\cos^4 u - 32\cos^2 u + 1$
9	$\cos(9u) = 256\cos^9 u - 576\cos^7 u + 432\cos^5 u - 120\cos^3 u + 9\cos u$

From Table II, the following equation can be obtained

$$T_m(z) = 2zT_{m-1}(z) - T_{m-2}(z). \quad (7)$$

Thus, it can be used to calculate the next polynomial with the previous two orders of it:

$$T_m(z) = \cos\left[m\cos^{-1}(z)\right], \quad -1 \le z \le +1, \quad (8)$$

$$T_m(z) = \cosh\left[m\cosh^{-1}(z)\right], \quad z < -1, z > +1. \quad (9)$$

Array structure has uniform spacing and non-uniform amplitude array factor, equations are given (10) to (11) where $2M$ is the number of elements, the wave number is $k = 2\pi/\lambda$, and the polar angle relative to the array axis is θ:

$$(AF)_{2M} = a_1 e^{+j(1/2)kd\cos\theta} + a_2 e^{+j(3/2)kd\cos\theta} + \ldots + a_M e^{-j[(2M-1)/2]kd\cos\theta} = 2\sum_{n=1}^{M} a_n \cos\left[\frac{(2n-1)}{2}kd\cos\theta\right], \quad (10)$$

$$(AF)_{2M+1} = 2a_1 + a_2 e^{+jkd\cos\theta} + a_2 e^{+j2kd\cos\theta} + \ldots + a_{M+1} e^{-jMkd\cos\theta} = 2\sum_{n=1}^{M+1} a_n \cos\left[(n-1)kd\cos\theta\right]. \quad (11)$$

These Dolph-Tschebyscheff distribution array factor (AF) equations are implemented to optimise the antenna array structure in the GA and DL.

IV. GENERATING DATA USING GENETIC ALGORITHM

The dimensions length, width, height, the number of antenna elements in the array, and spacing between these elements constitute a chromosome. For a 32-bit chromosome, five bits are used for length of the microstrip antenna, five bits used for width of the microstrip antenna, ten bits used for height of the microstrip antenna, seven bits used for spacing between elements of the array, and the four bits are used for element count given in Fig. 2. Hence 31 bits are used in the 32-bit chromosome and one bit is reserved for redundancy. If necessary, it will be used for any part of the chromosome; however, there is no longer a necessity. For the thickness small values are needed, so more bits have been allocated to the thickness.

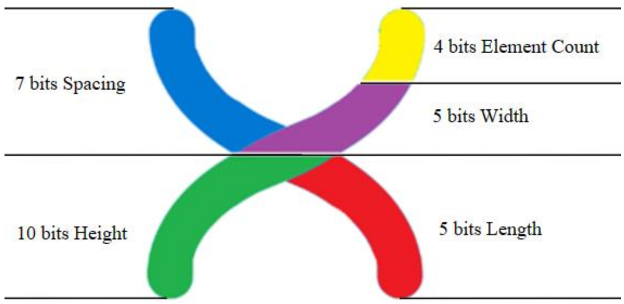

Fig. 2. The chromosome structure.

The flow chart of the GA, which starts with generation initial population, is given in Fig. 3.

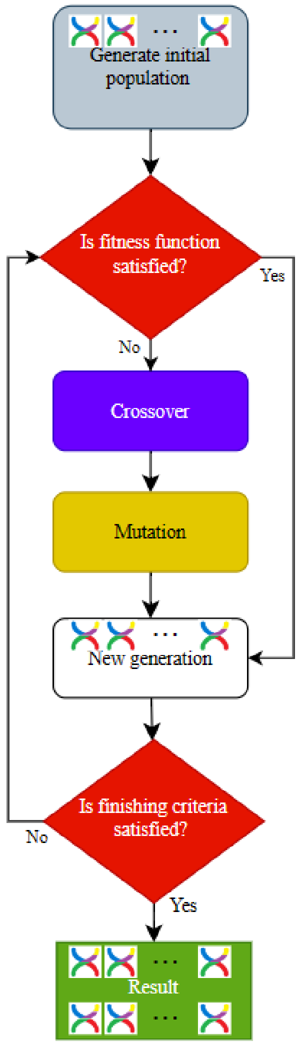

Fig. 3. Genetic algorithm flow chart.

The first population is created at random. The crossover mechanism is applied to the parents randomly selected from this population. The mutation mechanism is applied and a new generation is produced with a probability. The new individual is added to the new generation. The new generation is tested using the fitness function and, if it is satisfied, the chromosome is added to the new generation. The fitness function, which is given in (12), is determined based on the desired parameters in the antenna array, such as bandwidth

(BW), fractional bandwidth (FBW), the resonant frequency f_r of the antenna structure, the constants X and Y are determined by the user, and N is the number of elements in the antenna structure

$$Fitness\ \ function = FBW \times \frac{BW}{f_r} \times \frac{X}{Y+N}. \tag{12}$$

Thus, crossover and mutation applied generations are added to the new generation. If the finishing criteria are satisfied, new generations are used for the next step. The final result is the optimised antenna specifications.

V. PROPOSED DEEP LEARNING APPLICATION

As mentioned above, DL algorithms are very popular in antenna array design. Therefore, fully connected (FC) multilayer perceptron (MLP) and DL algorithms are used. The architecture of the proposed model consists of an input layer, up to 20 hidden layers for DL, and an output layer. The activation function of this model is rectified linear unit (ReLU), which is given in (13) and (14) and Fig. 4:

$$y(x) = \max(0, x), \tag{13}$$

$$y'(x) = \begin{cases} 0\ if\ \ x < 0, \\ 1\ if\ \ x \geq 0. \end{cases} \tag{14}$$

The effective computational properties of the activation layer ReLU enables the neural network to learn rapidly. When the input x is below zero, the gradient of the function becomes zero, which makes the network avoid backpropagation.

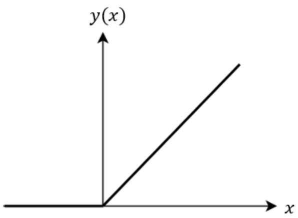

Fig. 4. ReLU function.

The number of layers and neurons used in each layer is established by the input data. If too small numbers are determined for layers or neurons, this causes unsuccessful learning; on the contrary, too large numbers cause overfitting, and the results will be the same. This may cause the prediction of the unknown result to be unsuccessful. To avoid this situation, a comparison is made. The same configuration is used with changing number of layers, and the lowest mean squared error (MSE) (%) is investigated.

The comparison of the neural networks with different layer size structures under the other same conditions is given in Fig. 5. MSE of the structure with five hidden layers has the smallest error. Thus, the final architecture of the proposed DL model includes five hidden layers, the input layer with five neurons, the others include 512 neurons per layer, and the output layer includes one neuron. The architecture of the proposed DL model is shown in Fig. 6.

In the input layer, scaling is used to change the antenna parameters to bits. For the deep learning model, 1024 GA generated antenna array samples are used. All hidden layers are fully connected, and the ReLU activation layer is used. The optimiser used in DL is chosen as adaptive moment estimation (Adam) due to its advantages of adaptive learning rates, computational efficiency, and low memory requirements [18].

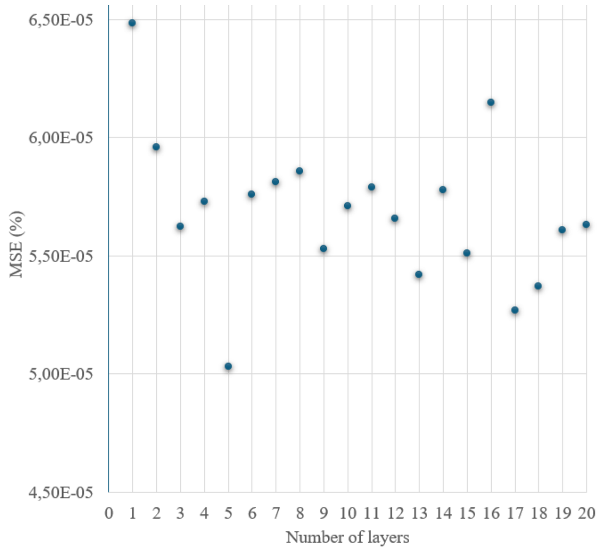

Fig. 5. Variation of MSE with the number of hidden layers.

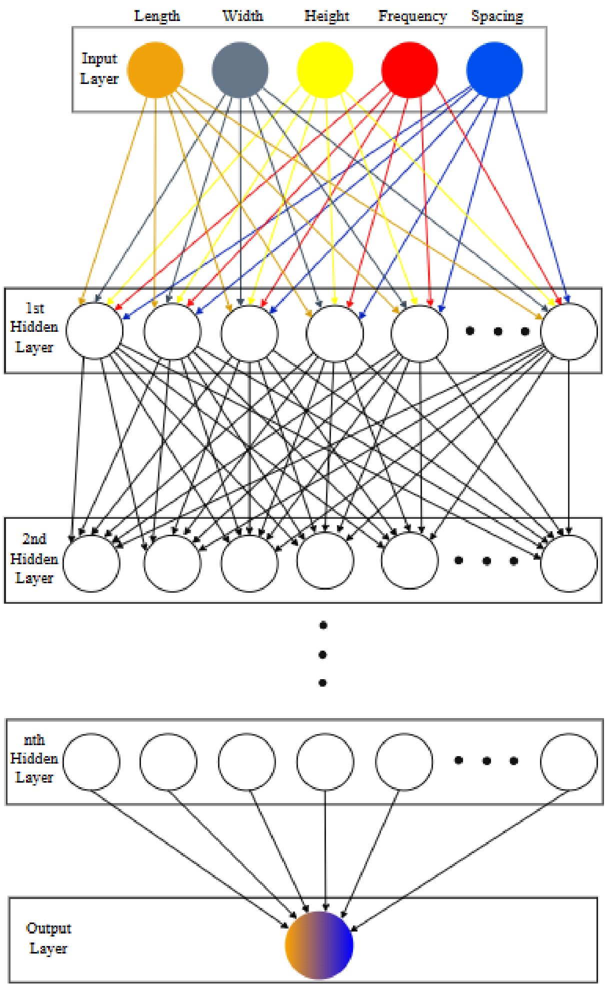

Fig. 6. Architecture of the proposed deep learning model.

In the proposed deep learning model, the GA generated data set is used for training and testing data. Training has been completed in 1000 epochs. The model is trained for a %80 number of epochs on the training data, and its performance is evaluated with validation data. After the training of the DL model is executed, %20 of the data set is used for test data. The errors of the testing data are analysed.

In the feedback mechanism, the errors analyses and the test data are used for the evaluation. All these analyses are input to the training. Later, the proposed model is applied to new data, and this process gives the prediction. The block diagram of the proposed DL model is given in Fig. 7.

Recent advances in DL have shown promising results in various antenna array optimisation problems [19]–[23]. However, the integration of GA generated inputs into deep learning models has not yet been adequately tried in antenna array optimisation before.

The proposed model contains three phases. The first phase, data generation for DL, is shown in Fig. 3; second phase, the proposed DL application that extracts high-level features from the input data and makes prediction, is given in Fig. 6 (in this phase, the initial solutions provided by the genetic algorithm are further developed to produce more precise and optimised predictions). The third phase, the Dolph-Tschebyscheff distribution phase, applies the Dolph-Tschebyscheff distribution to further improve the results obtained from the deep learning model. This distribution controls the side lobe levels (SLLs) of the antenna array, providing a balance between the width of the main lobe and the suppression of the side lobe.

In this proposed integrated model of complex algorithms, the results are aimed to be even better. Thus, the final antenna array pattern exhibits optimal performance at both high fidelity and low SLLs.

The output of the first phase is used as input for the second phase and the output of the second phase is used as input for the third phase. This situation is together shown in Fig. 8. These block diagrams together become the proposed model block diagram, which is given in Fig. 8.

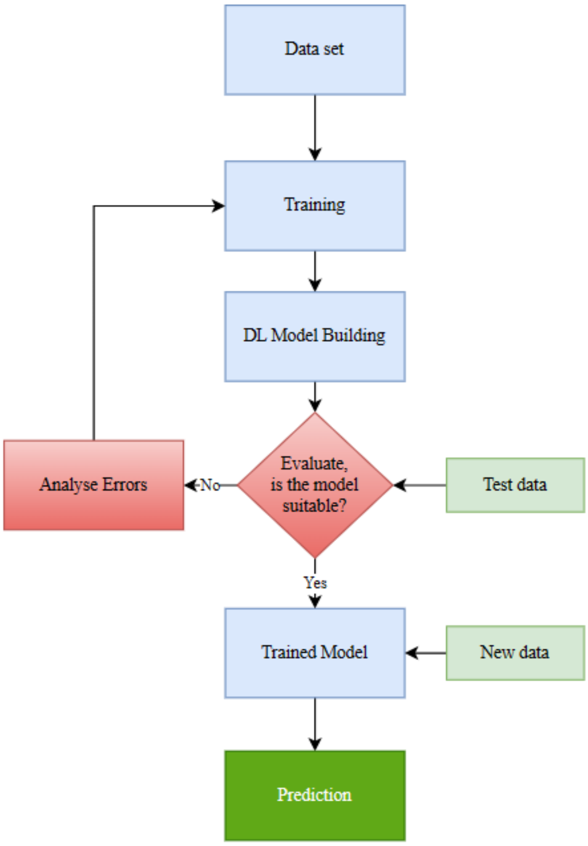

Fig. 7. Block diagram of the proposed DL model.

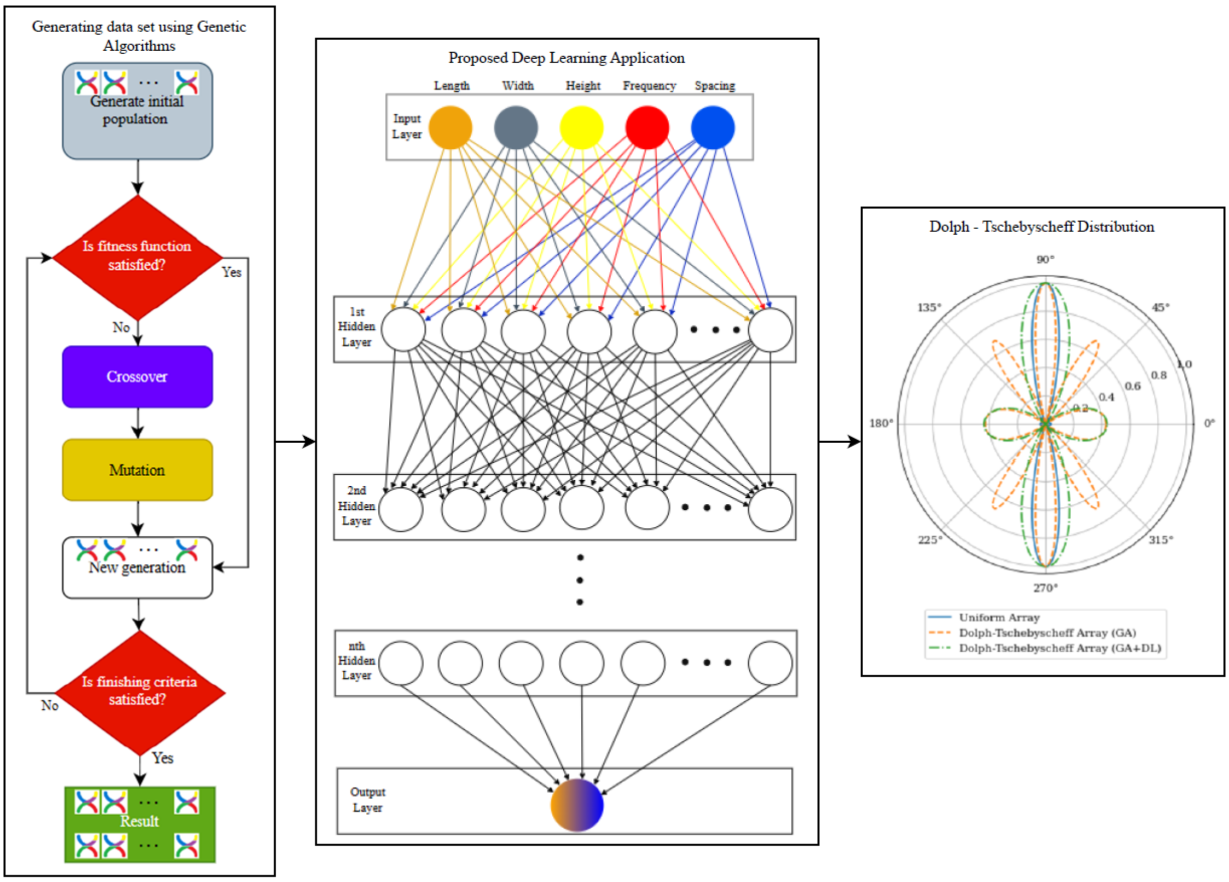

Fig. 8. Block diagram of the proposed model.

The pseudocode of the integrated model of the proposed algorithm is given in Fig. 9.

```
Require: Initial data, training and testing data,
input antenna array
Ensure:  Comprehensive  results  from  genetic
algorithm,  deep  learning  model,  and  Dolph
Tschebyscheff distribution analysis

Phase 1: Genetic Algorithm for Data Generation
Function GeneticAlgorithm(initialData)
Population←SelectChromosomes(population)
repeat
selectedChromosomes←SelectChromosomes(populatio
n)
crossedOver←CrossOver(selectedChromosomes)
mutated←Mutation(crossedOver)
population←CreateNewGeneration(mutated,selected
Chromosomes)
  untilFitnessCriteriaSatisfied(population)
  return population
end function

Phase 2: Deep Learning Application
function
DeepLearningProcess(trainedData,testData)
for epoch in epochs do
Train model on trainData
errors←Evaluate(model,testData)
end for
testResults←model.Test(testData)
Analyze errors and testResults
predictions←ApplyModel(model,newData)
return simulationResults
end function

Phase   3:   Dolph-Tschebyscheff   Distribution
Analysis
function DolphTschebyscheffProcess(inputArray)
analyze input Array
distribution←CalculateDolphTschebyscheff(inputA
rray)
arrayFactor←CalculateArrayFactor(distribution)
radiationPattern←CreateRadiationPattern(distrib
ution)
simulationResults←Simulate(radiationPattern)
Compare simulationResults with expected results
Return simulationResults
end function
```

Fig. 9. Pseudocode of the proposed model.

The new data, which contain specifications of the antenna array structure applied in the DL, are given in Table III.

TABLE III. SPECIFICATIONS OF THE ANTENNA ARRAY STRUCTURE.

Specification	Parameter
Amplitude Distribution	Dolph-Tschebyscheff
Antenna Model	Microstrip patch
Frequency	28.13 GHz
Number of Elements	4
Spacing between the Elements (optimised with GA)	0,0052 m
Length	0,0095 m
Width	0,0095 m
Height	0,00062 m

The optimisation codes are implemented for GA in C++ and for the DL in Python. The computer used for the computations has a 64-bit operating system with an Intel i7 processor at 2.80 GHz and 16 GB RAM. Compiling the code takes about for GA 60 min, for DL 5 hidden layers, 60 min.

VI. RESULTS

In this paper, the GA generated data set is used for a DL antenna design methodology. The data set includes the antenna parameters as input features of the DL. For a desired performance of the antenna array, the Dolph-Tschebyscheff distribution is used. The array structure's performance is compared by computing the radiation patterns and gains for the uniform array, the Dolph-Tschebyscheff array, and the proposed model. The result obtained on the training and validation sets shows that the model can make the estimation with high accuracy as given in Figs. 10 and 11. This makes an important contribution to the process of optimising the antenna array parameters in the design.

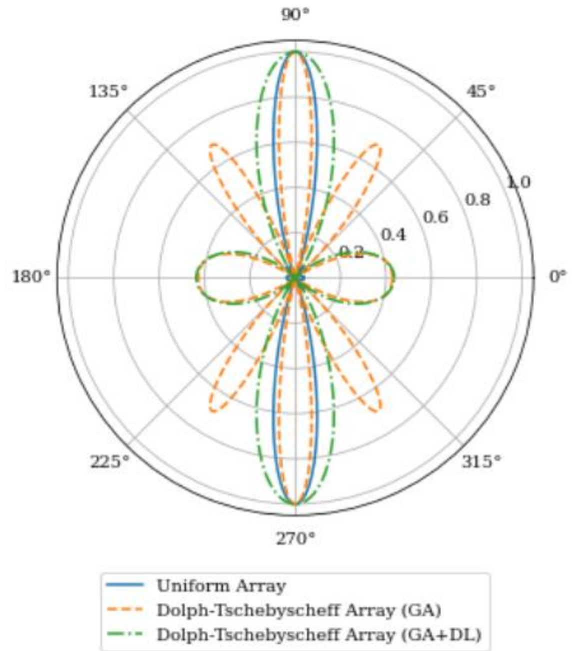

Fig. 10. Comparison of the structures Radiation Pattern.

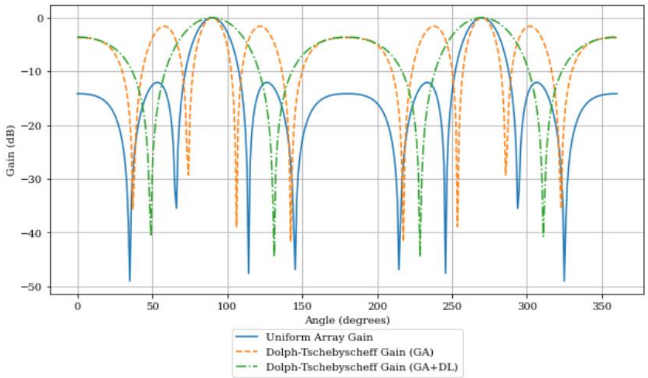

Fig. 11. Comparison of the structures Gain.

Although the GA-generated arrays offered improved side lobe levels (SLLs) compared to traditional uniform arrays, the results obtained with DL integration showed improved performance. The main reason for this improvement is the capacity of the DL model to create more complex and effective patterns by learning from GA outputs. In addition, the proposed GA+DL method is able to reduce SLL without a significant increase in the width of the main lobe, which improves the focus of the radiation pattern in the desired direction.

Figures 10 and 11 show that SLL in the proposed GA+DL model is suppressed. This means the proposed model, combined use of GA and DL, is an effective method in antenna optimisation. When the discovery capabilities of GA are combined with the learning and generalisation capabilities of DL, better antenna array patterns can be obtained. This study demonstrates the potential advantages of the GA+DL approach in applications where SLLs are critical.

VII. CONCLUSIONS

A DL-based model is designed to improve the characteristics of the Dolph-Tschebyscheff distributed antenna array structure. In this study, a four-element linear antenna array with uniform spacing and non-uniform amplitudes is used. Then, a GA was created with mutation and crossover mechanisms and initialised with a random initial population. The results validated that the proposed DL algorithm based on the samples generated by the GA provides better radiation pattern characteristics than the original spaced Dolph-Tschebyscheff distributed antenna array structure and uniform array. This offers significant advantages, such as low side lobe levels.

For future studies, it is anticipated that antenna performance using the DL-based methodology can be extended to other wireless communication technologies such as spacecraft, the Internet of Things (IoT), the Internet of Vehicles (IoV) [24], and Vehicle-to-Vehicle (V2V) [25] communication. This proposed GA+DL model will contribute to the development of more efficient and reliable communication systems in related technologies.

The results of this study reveal that the integration of DL and GA is a powerful tool for antenna array design and constitutes an important reference for future research.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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