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INTELLIGENT MATCHING TECHNIQUE FOR FLEXIBLE ANTENNAS

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Abstract. Flexible antennas have revolutionized the wireless communication as integral components of modern smart devices. Their unique properties are design flexibility, enhanced performance, and seamless implementation in smart devices. However, when designing antennas, multiple conflicting objectives often need to be considered simultaneously. Incorporating artificial neural networks into optimization strategies has shown promising results in antenna design problems. Neural networks can adapt to different and changeable requirements and constraints. That is why they are valuable tools for customizing antennas to specific operating conditions. The utilization of artificial neural networks for the design of flexible antennas enables researchers to expand the design space, optimize antenna characteristics with greater efficiency, and identify innovative solutions that may not be apparent through traditional design methods. In this study, the authors propose to determine required parameters and characteristics of flexible antennas by using Artificial Intelligence techniques, namely fuzzy logic, neural networks, and genetic algorithms. A matching technique based on neural network for designing flexible antennas has been elaborated. A neural network was developed. To train the neural network, several samples of flexible antenna were manufactured and tested. The developed neural network was simulated. Finally, the obtained flexible antenna was tested.

Keywords: flexible antenna, wearable device, neural network

INTELIGENTNA TECHNOLOGIA DOPASOWYWANIA DLA ELASTYCZNYCH ANTEN

Streszczenie. Elastyczne anteny zrewolucjonizowały komunikację bezprzewodową jako integralny element nowoczesnych inteligentnych urządzeń. Ich unikalne właściwości obejmują większą elastyczność projektowania, zwiększoną wydajność i bezproblemowe wdrażanie w inteligentnych urządzeniach. Jednak przy projektowaniu anten często konieczne jest jednoczesne uwzględnienie kilku celów, które są ze sobą sprzeczne. Zastosowanie sztucznych sieci neuronowych w strategii optymalizacji dało już obiecujące wyniki w problematyce projektowania anten. Sieci neuronowe potrafią dostosowywać się do zmieniających się wymagań i ograniczeń. Dlatego są one cennym narzędziem do dostrajania anten do konkretnych warunków pracy. Wykorzystanie sztucznych sieci neuronowych do projektowania elastycznych anten pozwala naukowcom rozszerzyć przestrzeń projektową, zoptymalizować charakterystykę anteny z większą wydajnością i ujawnić innowacyjne rozwiązania, które mogą nie być oczywiste przy użyciu tradycyjnych metod projektowania. W pracy autorzy proponują wyznaczenie niezbędnych parametrów i charakterystyk elastycznych anten z wykorzystaniem metod sztucznej inteligencji, czyli logiki rozmytej, sieci neuronowych i algorytmów genetycznych. Opracowano technikę dopasowywania opartą na sieci neuronowej do projektowania elastycznych anten. Opracowano sieć neuronową. Wyprodukowano i przetestowano kilka próbek elastycznych anten na potrzeby uczenia sieci neuronowej. Wykonano symulację opracowanej sieci neuronowej. Na koniec przetestowano powstałą elastyczną antene.

Slowa kluczowe: elastyczna antena, urządzenia ubieralne, sieć neuronowa

Introduction

A great innovation in engineering is the technology of flexible antennas that may be applied in various cases [11]. Flexible antennas play a crucial role when being integrated into smart wearable devices like smartwatches or fitness trackers by enabling reliable wireless communication without compromising user's comfort or design aesthetics or device's functionality. Another important application is in IoT sensors where space is limited, such as special medical devices. The flexibility of these antennas enables optimizing their placement for sufficient signal receiving due to improved frequency range. Thus, flexible antennas can be regarded as essential components in devices of wireless systems where traditional rigid antennas are not practical due to their ability to conform to various shapes and surfaces.

Despite many benefits, flexible antennas also present challenges for the performance optimization. Flexible antennas are constructed from bendable materials, such as polymers or composites, so they are able to bend to various surfaces without losing functionality [2]. The performance of the antenna in terms of bandwidth, efficiency, and radiation pattern can be greatly impacted by bending radius, material characteristics, and mechanical stress an so on. Moreover, maintaining mechanical integrity while being flexible is a technical issue that requires innovative solutions both in material science and in design engineering. The design of flexible antennas presents a number of unique challenges in comparison to the design of rigid antennas. Traditional design methods frequently are labor- and time-intensive procedures.

Artificial Intelligence (AI) are revolutionizing the way complex problems get solved and processes designed. AI algorithms can analyze vast amounts of data and identify complex patterns [4]. These capabilities simplify the process of solving problems across a vast range of engineering specialties. AI can be employed to optimize designs by means of simulations, explorations of design spaces and the identification of optimal solutions in accordance with specified criteria. This approach facilitates the generation of more efficient and innovative designs, thereby reducing the time and costs associated with iterative design processes.

1. Literature review

Integral components of Artificial Intelligence are fuzzy logic systems, artificial neural networks, genetic and evolutional algorithms. These techniques play crucial roles in enhancing the capabilities of AI systems by enabling them to learn, reason, adapt, and optimize solutions in various applications. Application of fuzzy logic systems to technical problems provides a flexible reasoning approach that effectively handles uncertainties and imprecise data [9]. Utilization of artificial neural networks, inspired by the human brain's neural connections, enables machines to learn from data, recognize patterns, and make decisions to practical problems and to adapt autonomously [16]. Use of genetic algorithms offers an evolutionary perspective, inspired by the principles of natural selection, provides optimal solutions to scientific problems through iterative processes like selection, crossover, and mutation [29].

In recent years, neural networks have been regarded as powerful tools for optimizing the design of flexible antennas. The effectiveness of neural networks in antenna design optimization to attain better performance characteristics has been shown in numerous studies and substantiated through comprehensive simulation and practical experiments. One of the principal advantages of utilizing neural networks in the field of antenna design is their ability to learn complex patterns from data. By training neural network models on datasets of antenna geometries and electromagnetic properties, it is possible to predict optimal configurations for specific applications. This approach enables rapid prototyping and fine-tuning antennas, with minimal human intervention [20]. The incorporation of neural network approach for adaptive signal processing enables antenna arrays to dynamically adjust their radiation patterns in real time, thereby optimizing signal reception

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This work is licensed under a Creative Commons Attribution 4.0 International License. Utwór dostępny jest na licencji Creative Commons Uznanie autorstwa 4.0 Międzynarodowe. and mitigating interference [5]. The main advantage of neural networks is that they can perform multi-objective optimization by learning complex relationships between design parameters and performance metrics [8]. The integration of neural networks with other techniques, such as genetic algorithms or particle swarm optimization, enables achieving superior antenna performance compared to traditional methods [28].

The authors have carefully examined the relevant works in the area of antenna design. Utilization of artificial intelligence techniques had been widely investigated. Studies have demonstrated significant enhancements in antenna performance metrics such as gain, bandwidth, and efficiency in comparison to traditional design methods [29]. However, some gaps are still remained.

Thus, paper [8] proposes a new method for finding the optimal design of a broadband microstrip antenna device using a neural network. Nevertheless, the neural network is only discussed, not presented.

Work [26] considers how a neural network may be applied in the process of designing a microstrip antenna. However, it provides no mathematical background.

Study [13] proposed a methodology of designing a microstrip antenna, which was also evaluated by simulation in Matlab. But, in this study only two geometric parameters of the antenna are regarded as outputs of the neural network, that is not always enough.

Artificial neural networks are proposed in [14] to be used to estimate the initial structure of antenna. Nevertheless, in this case the optimized characteristics were close to the requested ones, but the match was not perfect.

Study [21] argues that an artificial neural network is a best method among other optimization methods for designing smart antennas. However, the outcome of simulation is a beam forming, not resonance frequency.

Paper [32] proposes a modelling method based on convolutional neural networks for optimizing the design of a multiband microstrip antenna. Only simulation results were considered, by not the process of simulation.

Antenna performance parameters are optimized due to the fuzzy inference system in [6]. But, in our enquiry, we need to optimize geometric, not performance parameters.

Paper [19] presents approach for choosing the optimum antenna type and providing the best geometric characteristics based on fuzzy controllers. However, this approach does not provide a resonance frequency optimization.

A genetic algorithm is employed in [18] in order to demonstrate how the optimal design of an antenna structure can be searched out. However, for some specific cases, not the optimal antenna design, but the optimization of the existing design is required.

Some studies suggest using composite or hybrid approaches.

Paper [30] discusses an antenna design method, where a neural network is combined with other optimization techniques. The drawback is that method is quite complicated.

In [10] a neuro-fuzzy method is suggested for estimation of the operating frequency of antennas. However, no precise data on the neuro-fuzzy model are given.

A hybrid technique for designing antennas which combines a neural network with a genetic algorithm was introduced in [12]. Usefulness of the investigation is hard to evaluate due to its shortness.

A technology for designing antennas combining neural networks with both fuzzy logic and genetic algorithms is considered in [18]. The technology itself was promising not fully elaborated.

Thus, we can conclude that by harnessing the power of artificial intelligence, the design process be can accelerated and the challenges associated with flexible antenna design can be overcome, and innovative solutions for next-generation wireless communication systems can be created. Despite the considerable advances made in the application of neural networks, fuzzy controllers and genetic algorithms to antenna design, a number of challenges still remain.

The authors can summarize that although utilization of AI methods had been researched deeply, most performed studies apply only neural network approach, while other techniques as fuzzy logic and genetic algorithms were investigated less. Next, according to [3, 7, 28] application of a hybrid technique combining a neural network with a fuzzy logic system and a genetic algorithm may be even more promising and effective than applying only one of these techniques. Moreover, some works lack either a fully elaborated methodology or more data provided on designing and simulation.

These drawbacks will be considered and overcome by the authors in this study.

2. Problem statement

Different wearable devices such as smartwatches, activity trackers, fitness bands, body sensors and others are becoming a part of every day's life for many peoples.

To be integrates properly onto the human body, the wearable devices must be physically flexible, bendable or even stretchable. Moreover, flexible electronic devices are practical, inexpensive, and environmentally friendly. The most significant module of a wearable device is the antenna as it determines efficiency of the whole wireless system. Flexible electronic devices imply the usage of flexible antennas operating in specific frequency bands to provide wireless connectivity needed for modern information-oriented society

That is why, the need for flexible antennas has increased in recent years. They have been widely employed in modern communication systems. Nowadays, the field of flexible antenna developments is rapidly enhancing due to demands for wearable devices.

However, a significant challenge arises when wearables need to operate in various countries with different LTE frequency bands. The incompatibility of wearable devices with flexible antennas developed for specific LTE bands is a significant challenge to the deployment of these devices for international manufacturers.

The point is, each country may employ its own set of LTE frequency bands allocated for wireless communication. For instance, in the United States bands 2, 4, and 12 are mainly utilized, while in European countries bands 3, 7, and 20 are applied. This difference in frequency bands is a problem for wearable device manufacturers who want to make products that can be used worldwide. Because, when a wearable device with a flexible antenna is designed in one country, it may not function optimally in another country due to different LTE frequency bands.

This discrepancy necessitates the modification of the antenna geometry to match with the specific frequency bands of the target region.

To solve this task effectively, the authors propose an approach that applies artificial intelligence techniques to predict the parameters and characteristics required for modifying the flexible antenna design to ensure their operability in another LTE frequency band.

By employing the capabilities of AI algorithms and machine learning models, manufacturers can facilitate the antenna design modifying process thus to guarantee its optimal performance in a particular frequency band.

In our case, AI can be utilized to analyze complex data sets to predict rapidly the most effective antenna modifications for different frequency bands.

This predictive prediction solution will allow manufacturers to efficiently and accurately customize flexible antennas for diverse frequency band scenarios, thus eliminating the need for the time-consuming and costly calculations and modelling.

For instance, consider a company based in the European Union has developed a wearable with a flexible antenna inside it, optimized for LTE bands 3 and 7. To introduce the product to the American market, the company can employ the suggested matching technology to modify the antenna geometry design for bands 2 and 4. By accurately predicting the required parameters for the new antennas, the manufacturing company ensures their rapid production without the need for extensive manual calculation, thus streamlining the product development process.

Flexible LTE antenna modification technique using AI prediction is an example of the creative opportunities that exist at the intersection of flexible, communicational and intelligent technologies.

We propose to predict parameters and characteristics of the readjusted flexible antenna by using Artificial Intelligence techniques, namely fuzzy logic, neural networks, and genetic algorithms.

Fuzzy logic is a technique for reasoning under uncertainty, it can be employed when there is no mathematical model of the process. It can be used when dealing with uncertain knowledge while a system shows dynamic nature. Neural networks are able to acquire, store, utilize expert knowledge and can learn new patterns. The main learning feature of neural networks is their adaptation to different changing conditions. A genetic algorithm is a search method, based on evolutionary principles. Genetic algorithms provide an accurate and fast solution for optimization problems. A better method can be derived when combining these three techniques. That is because the combination overcomes limitations of one technique and produces a relevant result for improving the quality of service.

In the area of antenna design, the combination of fuzzy logic, neural networks, and genetic algorithms may offer significant advantages over using only one technique. Thus, fuzzy logic allows for handling uncertainty and imprecision in the design parameters, making it well-suited for complex, real-world RF environments. Neural networks can learn patterns from vast amounts of data, providing the ability to predict the antenna performance with high accuracy. Meanwhile, genetic algorithms can improve parameters of both the neural network and fuzzy system. Hybrid systems combining fuzzy logic control, neural networks, and genetic algorithms have proved their efficiency in a wide range of tasks.

By integrating these methods, antenna design and optimization become more adaptive, efficient, and capable of overcoming the limitations of each individual approach.

So, the authors will discuss combination of the three techniques in this inquiry.

3. Background

Scientists from Vinnytsia National Technical University (VNTU) have developed a flexible LTE antenna [22, 23, 25].

The flexible antenna (Fig. 1) works in two LTE frequency ranges B3 1800 MHz (Uplink 1710–1785 MHz, Downlink 1805–1880 MHz) and B20 800 MHz (Uplink 832–862 MHz, Downlink 791–821 MHz). The linear sizes of the antenna were 22×38 mm. The antenna was made of 0.3 mm thick polyamide. The peak power was 23 dBm.



Fig. 1. Developed flexible antenna

This antenna was designed for implementation in a wearable – the cellular lifesaving flexible device [15, 24]. This device was developed for a remote health control (Fig. 2).

During the research, different samples of the antenna had been tested. A set of experiments was carried out for several version of flexible antenna location in space – in the air, on a table,

and on an arm. The same experiments were performed to investigate flexible antennas when placed inside a rubber strap (Fig. 3).



Fig. 2. Sample of the cellular lifesaving flexible device



Fig. 3. Photo the short flexible antenna inside the rubber strap for experimental investigation

The original design of the antenna and its optimal coordination with a wearable device provided the reduction of the impact of capacitance and resistance of the antenna when the device's wristband was on an arm, thus ensuring a reliable communication with the wearable device in the LTE (or NB IoT) network.

But the problem is that different LTE frequency bands are employed in different countries. Thus, the wearable device with flexible antenna cannot be produced for some other counties, because it may not operate there due to different frequency bands. For that purpose, the designed in VNTU flexible antenna should be readjusted for other frequency LTE band.

The purpose of this study is to elaborate a matching technique based on a neural network to facilitate the process of designing new flexible antennas for other frequency bands.

4. Methodology

The first stage in applying neural networks to antenna design is to create a dataset of main parameters: antenna geometries, operating frequencies, material properties, performance metrics. Next step is designing a neural network architecture, that involves choosing the appropriate network structure, activation functions and algorithms to train the network effectively. So, the neural network is trained on the collected dataset to learn the correlations between the antenna parameters. After the successful training, the neural network can predict the performance of new antenna designs. The trained neural network is validated using a separate dataset to assess its performance in predicting antenna parameters accurately. If needed, the model can be adjusted to improve its accuracy.

Once the neural network is trained and validated, it can be utilized for antenna design optimization. The model is capable of generating novel antenna designs based on specified requirements, offering potential solutions that may not have been considered by engineers.

The artificial neural network is an information processing system that does not require the selection of a mathematical model in advance; instead, it uses an input-output of sample patterns and a set of activation functions (Fig. 4).



Fig. 4. Artificial neural network

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An input layer, one or more hidden layers, and one output layer typically exist in multilayer networks. The input layer receives the initial values, the hidden layer performs the computations, and the output layer receives the activated values, where each pattern is assigned a particular classification category. The layers can be represented as vectors:

$$x = [x_1, x_2, ..., x_n]^t$$

$$y = [y_1, y_2, ..., y_p]^t$$

$$O = [O_1, O_2, ..., O_m]^t$$

The neural network is trained via gradient descent, and the output layer and hidden layer receive the calculated error for weight adjustments. Two sets of weights exist in a neural network: those from the input layer to the hidden layer and those from the hidden layer to the output layer. The delta rule is used to determine the error resulting from the second set of weights. In order to assign the error proportionately to the weights that created it, the error must propagate from the output layer to the input layer.

A backpropagation neural network (BPNN) is one of the most frequently utilized techniques for learning both linear and nonlinear functions [31]. It employs a supervised learning method and a feed-forward structure for computer learning and modelling. It is well established that a single hidden layer is sufficient for approximation of a continuous function with arbitrary precision.

A backpropagation algorithm consists of multiple iterations – epochs. Each epoch consists of two passes:

1. Forward pass: this technique takes an input vector, computes a function, and assesses the error function's derivative in relation to weights.

2. Backward pass: it computes the weight adjustments and propagates the error derivatives backward.

In order to calculate the net input to the neuron, each input connected to the neuron is multiplied by its corresponding weight, thereby forming a weighted sum. This sum is then added to the bias associated with the neuron j [27].

The net input n_i to neuron j is

$$n_j = \sum_i w_{ij} \cdot f_i + b_j \tag{1}$$

where w_{ij} is the weight of a synapse from neuron *i* to neuron *j*, f_i is the output of neuron *i*, b_j is the bias of neuron *j*.

In each neuron, the weighted inputs from other neurons and a bias term are summed. The sum is then applied to the activation function.

A bias may be regarded as a connection weight from some neuron with a constant activation value. An activation function is employed to transform the output variable, ensuring that it falls within an acceptable range. It is theoretically possible to utilize any differentiable functions as an activation function. The most commonly employed types of activation functions are linear, sigmoid and hyperbolic tangent.

The input layer of the network receives the set of training patterns at the start of training. The training pattern is applied to the input layer during the forward pass, and the network experiences its effects. The network's synaptic weights are entirely fixed throughout the forward pass. Conversely, the weights are modified in line with an error-correction rule during the backward phase.

The actual output value of the network is subtracted from the desired one to produce an error signal. The actual output of the network is subtracted from the desired output, which is part of the training, to produce an error signal. This error signal is then sent backwards through the network, in the opposite direction to the synaptic connections. The weights are adjusted so that the actual output of the network moves closer to the desired output. The error function E can be defined as [1]:

$$E = \sum_{l=1}^{m} (O_l - D_l)^2$$
 (2)

where *m* is the number of output vector, O_l is the actual output vector, D_l is the desired output vector.

The error function's gradient with respect to the weighting vector is as follows:

$$g_k = \frac{\partial E}{\partial w_k} \tag{3}$$

where k is the iteration index, w_k is the current weighting vector.

Next, the update to the weighting vector in error backpropagation is:

$$w_{k+1} = w_k - e \cdot g_k \tag{4}$$

where w_{k+1} is the next weighting vector, e is the learning rate parameter. Overly high learning rate can cause oscillations and instability in the algorithm. However, if the learning rate is too low, it'll take the algorithm too long to converge. The main drawbacks of traditional BPNN are that it takes a long time to learn and it can get stuck in a local minimum.

5. Experimental results

During the investigation, three experiments were conducted, each with a different example of the flexible antenna (Fig. 5, 6). The cases that provided the best results were be considered.



Fig. 5. Samples of the flexible antenna

The influence of the upper part length of the antenna radiating part on SWR frequency characteristics was investigated. Here, the upper part of the antenna (the radiating surface) was shortened by cutting it off several times.

The influence of the lower part length of the antenna was investigated. Here, the lower part of the antenna (the shielding surface) was shortened by cutting it off several times. Best results were achieved when the lower part of the antenna became 7 mm long and the SWR in the LF area returned to its reference shape

The influence of the central strip of the antenna radiating part on SWR frequency characteristics was investigated. Here, the central strip of the antenna was shortened by cutting it off several times. Best results were achieved when the central strip length was 17 mm. This is the most optimal version for ensuring characteristics in the B8 frequency band.



Fig. 6. Investigation of flexible antennas

6. Simulation results

So, when designing a new flexible antenna for other frequency band, the first step is to predict its parameters by applying the neural network (also, hybrid methods – neural-fuzzy of neuralgenetic can be applied). Thus, this matching technique facilitates the process of designing the new flexible antenna.

Data for the neural network was gathered via measurements. In most cases, data samples are first split into three groups: training (used at a 70% ratio), testing (15%), and validation (15%). Variations in percentages may occur depending on the requirements of a certain application. In our case, the authors propose to split samples into two groups: 70% for training and for 30% testing. The size of the network is then selected, i.e., the quantity of neurons and hidden layers in each one. In order to train the neural network and create the model, the algorithm is ultimately chosen.

In this study, a backpropagation neural structure was chosen as it is one of the most frequently utilized neural networks for learning both linear and nonlinear functions. This type of network applies a supervised learning method and feed-forward structure for modelling.

During the training, the weights of connections in the network are adjusted by using the gradient descent method, so the measure of differences between the actual output of the network and the desired output can be minimized.

Accurate data must be used to train the model in order to have the lowest mean squared error (MSE). Different algorithms have been evaluated by varying the number of hidden layers and neurons in each hidden layer in an attempt to MSE. Ultimately, the optimal configuration for the suggested model was chosen.

The suggested model, which uses the train set to forecast the resonant frequency, is depicted in Fig. 7. It takes as input values geometrical antenna parameters, such as upper part length, central part length and lower part length.



Fig. 7. Proposed al network model for synthesis of a flexible antenna

The developed in this study feed-forward backpropagation neural network (FFBPNN) employed the six-layer neural network configuration with four hidden layers.

There are three neurons at the input layer as one regarded three geometric parameters of the flexible antenna, namely upper part length, lower part length, central strip length. The output of the FFBPNN is its resonance frequency.

The neural network was created using the Levenberg-Marquardt (LM) back propagation technique. The output layer is made of 1 neuron, while each hidden layer consists of 27 neurons. The MATLAB R2014 neural network tool box was used to train the FFBPNN model. The layout of the FFBPNN is given in Fig. 8.

27 neurons in hidden layers were chosen as optimal quantity that showed the best results in training. Hyperbolic tangent sigmoid transfer function was used in the all layers of the experiment. 70% of the collected during experiments dataset was used for the training of FFBPNN and the remaining 30% was used for its testing.

The weights of connections adjusted during the training process are shown in Fig. 9. Fig. 10 displays training performance curves of the neural network for training, testing, validation, and overall procedure.

During the study and simulation, feed-forward backpropagation neural networks showed better results than cascade forward networks. Results of testing are shown in Fig. 11.

The proposed matching technique is expected to provide better results with the smallest errors for enhanced datasets.

Algorithms		<i>B D D D D D D D D D D</i>	1	
Data Division: Rand	dom (divid	derand)		
Training: Leve	nberg-Mar	quardt (trainIm)		
Performance: Mea	n Squared I	Error (mse)		
Calculations: MAT	LAB			
Progress				
Epoch:	0	7 iterations	1000	
Time:		0:00:08]	
Performance:	307	0.000333	0.00	
Gradient:	6.70e+03	19.1	1.00e-07	
Mu:	0.00100	0.0100	1.00e+10	
Validation Checks:	0	6	6	
Plots				
Performance	(plotperf	orm)		
Training State	Training State (plottrainstate)			
Regression (plotregression)				
Plot Interval:		1 epochs		
•				
Opening Perfo	ormance P	lot		

Fig. 8. Neural network architecture to train antenna parameters

View Train Simulate Adapt Reinitialize W/ Select the weight or bias to view: iw(1,1) - We 2.0052.2.4932.2.4762; 1.6695.2.801.2.6507; 2.1396.2.3799.3.003; 0.09211.2.3501.3.488; 2.993.3.0862.7.301;	eights View/Ed	dit Weights from input 1 、			
Select the weight or bias to view: iw{1,1} - We 2.3052 2.4932 2.4762; 1.6695 -2.801 -2.6507; 2.1396 2.3799 -3.003; 0.09211 2.3501 3.488; 2.9853 2.405, 2.75011-	eight to layer 1 f	from input 1 🕓	r		
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0.7223 5.0417 2.7252; 1.3793 - 3.622 - 2.0775; 2.4793 - 3.022 - 3.7789; 4.4793 - 3.022 - 3.7789; 4.4793 - 3.022 - 3.7789; 3.4793 - 3.022 - 3.7784; 3.4797 - 4.3225 - 1.5784; 1.4755 - 3.1806 - 0.4722; 0.5796 1 - 3375 - 3.3794; 0.5796 1 - 3375 - 3.3794; 0.5797 - 1.4996 - 3.4117; 0.5396 - 0.4115 - 0.7790 1.4032; 0.4115 - 0.7790 1.4032; 0.4135 - 0.7996 1.4032; 0.4136 - 0.7801 0.4032; 0.4136 - 0.7801 0.4032; 0.4146 - 0.7802; 0.4146 - 0.7802; 0.4147 - 0.4147; 0.4147 - 0.					

Fig. 9. Weights of connections in the neural network after training







Fig. 11. Network outputs after testing

7. Discussion

Overtraining the neural network can seriously deteriorate the forecasting results. This may be caused not only by processed data but by parameters of the network.

Therefore, genetic algorithms can be applied to tune such network parameters as epoch number, learning rate, number of hidden layers, types of activation functions on each layer etc.

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The user can choose some parameters for a better effectiveness of the network and test them by a genetic algorithm. This provides finding the most suitable architecture of the network that will solve the problem with minimum errors.

Genetic algorithms operate with encoded parameters. A chromosome represents a solution encoded into genes. Here, a gene corresponds to a network parameter. The proposed encoding of the neural network into a chromosome is shown in Table 1.

The type of activation functions is encoded as 0, 1, 2 which corresponds to sigmoid, rectified linear unit, and hyperbolic tangent. Using the genetic algorithm, the problem of finding the optimal architecture of neural network can be solved much faster.

Table 1. Proposed encoding for chromosomes

layers	neurons	activation functions
2	30, 30	2, 2,
3	15,12, 3	2, 1,1
4	24, 24, 24, 24	1,1,1,1

To give a better solution to the optimization problem, the artificial neural network can be combined with a fuzzy system. An adaptive neuro-fuzzy inference system (ANFIS) is a neural network operating like a fuzzy system under uncertain conditions, combining both fuzzy logic and neural networks principles. Thus, it can process nonlinear and complex systems. ANFIS is capable to approximate functions. For developing an adaptive neuro-fuzzy inference system, its linguistic variables, their terms as well as membership functions should be defined. Input variables describe all the possible states of a process and its output variable describes all possible actions. Then, a rule base should be assigned consisting of a set of IF-THEN rules to describe possible states.

For our case, input linguistic variables are three geometric parameters of the flexible antenna – upper part length, lower part length, central strip length. Its output variable is its resonance frequency.

Input variables are transformed into membership function values, a fuzzy output is evaluated according to a rule base, then the fuzzy output is converted to a crisp one. For our case, the input linguistic variables are defined with terms "short", "medium", "long". The output linguistic variable is defined with terms "very low", "low", "medium", "high", "very high". The rule base has 27 IF-THEN rules, as shown in Table 2.

Table 2. Rule base

Rule	Upper part	Lower part	Central strip	Resonance
number	length	length	length	frequency
1	short	short	short	very high
2	short	short	medium	very high
3	short	short	long	very high
4	short	medium	short	very high
5	short	medium	medium	very high
6	short	medium	long	high
7	short	long	short	high
8	short	long	medium	high
9	short	long	long	high
10	medium	short	short	high
11	medium	short	medium	high
12	medium	short	long	medium
13	medium	medium	short	medium
14	medium	medium	medium	medium
15	medium	medium	long	medium
16	medium	long	short	medium
17	medium	long	medium	low
18	medium	long	long	low
19	long	short	short	low
20	long	short	medium	low
21	long	short	long	low
22	long	medium	short	low
23	long	medium	medium	very low
24	long	medium	long	very low
25	long	long	short	very low
26	long	long	medium	very low
27	long	long	long	very low

Obtained during the investigation results will be used to construct the membership functions for a fuzzy controller, which will be developed in the future study.

8. Conclusion

Flexible antennas represent an advancement in modern technology, enabling seamless wireless communication in a wide array of applications in wearable devices, Internet of Things sensors, and aerospace systems. Neural networks have been successfully applied to a wide range of antenna design problems in practical applications and have proven to be versatile and effective in handling a wide range of design difficulties, from optimizing antenna arrays for 5G communication systems to developing tiny and flexible antennas for Internet of Things devices. The application of neural networks in designing flexible antennas represents a significant advancement in the field of antenna engineering by ensuring their optimization and customization for specific use cases in modern communication systems.

Through neural networks designers can swiftly determine the optimal antenna configurations for different LTE frequency bands. minimizing time-consuming manual calculations and prototyping simulations. This predictive capability may significantly accelerate the production cycle for flexible antennas in diverse operational environments. The integration of AI techniques, such as fuzzy logic, neural networks, and genetic algorithms, has immense potential to revolutionize antenna design techniques. The predictive facilities of AI technique enable engineers to modify rapidly flexible antenna design geometry for operation in another LTE frequency band, thereby overcoming the challenges posed by international frequency variability. This innovative approach not only ensures market agility and scalability but also fosters a culture of continuous improvement and adaptability in the area of wireless communication technology.

In this study, several samples of a flexible antenna were made. Then, their characteristics were investigated. The results were used to build, train and test a neural network, which was applied in the proposed matching technique. The matching technique implies application of the neural network to predict parameters of designed flexible antennas. So, the developed hybrid antenna design methodology underlies the proposed matching technique, it differs from the existing ones by considering all three AT tools – fuzzy logic, neural network and genetic algorithm thus overcoming the drawbacks of each of them. The predicted by the neural network parameters were used to design the required flexible antenna tested in the Hague by company Montr B.V. (montr.nl).

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