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RESEARCH ARTICLE

Data Driven Surrogate Modeling of Phase Array Antennas Using Deep Learning for Millimetric Band Applications

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ABSTRACT Phased Array Antenna (PAA) technology plays an important role in fields such as radar, 5G and satellite or any application which requires wide bandwidth and high gain. However, achieving such design is a difficult and complex task that requires an accurate calculation and combination of results obtained for varying phase and amplitude of each unit and coupling effects between these elements of the PAA structure is a task that can only be obtained using full wave EM simulation tools. This comes at the price of a significant increase for the computational cost of the design process which is a well-known drawback of forward EM modeling of microwave stages most especially in case of repetitive analysis's such as yield analyses or optimization tasks. Data-driven surrogate models have emerged as a powerful and versatile solution that bridges the gap between computationally expensive simulations and rapid, reliable prediction models suitable for deployment in applications such as optimization and/or yield analyses. Herein, for having a high-performance broadband PAA for millimeter band in a computationally efficient manner, artificial intelligence based surrogate model assisted optimization approach is deployed. A series of state-of-the-art surrogate modeling algorithms are deployed to create a surrogate model of the studied PAA design for the prediction of radiation pattern characteristic with respect to the input phase values of each array element. As a result, a drastic reduction in computational time of almost 90% for the optimization of three PAA designs is achieved. Thus, the proposed approach offers promising avenues for further exploration in computational electromagnetics, most especially in simulation expensive problems with complex designs.

INDEX TERMS Artificial intelligence, data driven modelling, surrogate modelling, optimization, phased array antenna.

I. INTRODUCTION

Phased Array Antenna (PAA) technology plays an important role in the field of antenna technologies. While the PAA technology is constantly improving, it is also used extensively in applications such as radar, 5G and satellite [1], [2], [3], [4], [5], [6], [7]. In particular, phased array antenna designs that provide wide bandwidth and high gain in the millimeter band have many fields of study. For example, air, aircraft and defence radars, Ka band satellite communications, 5G radio link communications, etc. [8], [9], [10], [11], [12], [13], [14]. Satellite communication technology in the millimeter band has a lower cost of satellite service purchase and a higher data rate, especially compared to other frequencies [15], [16], [17]. Therefore, the Ka band comes to the fore, especially in the field of satellite communication. PAA designs are usually performed on the PCB in different antenna types such as patch, bow tie, Vivaldi, etc. [18], [19], [20], [21], [22]. One of the most important factors in choosing patch antennas is that they can be used with parasitic structures. Thus, unit antenna cells with high bandwidth and efficiency can be formed. This is especially advantageous in providing broadband and high

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gain, which is usually specified as whether in millimetric bands [23], [24], [25].

While designing the PAA, the goal is to design an antenna that provides broadband and high efficiency that can be used for a wide range of applications in the millimeter band. However, having such a design is a difficult and complex task. Accurate calculation and combination of results obtained for varying phase and amplitude of each unit and coupling effects between these elements of the PAA structure is a task that can only be obtained using full wave EM simulation tools. This comes at the price of a significant increase for the computational cost of the design process which is a well-known drawback of forward EM modeling of microwave stages [26].

In the field of computational-science and engineering, with the increasing complexity and high dimensionality of engineering problems, the need for having efficient and highly accurate modeling approaches have become a topic that being persuaded by many researchers [27]. As it mentioned before, traditional simulation-based models such as full wave EM simulators often require high computational resources (RAM, CPU power etc.) and simulation time which creates a significant challenge for time sensitive, decision making process requires repetitive analysis's such as yield analyses or optimization tasks [28]. An efficient solution method for this challenge is data-driven surrogate modeling. Data-driven surrogate models have emerged as a powerful and versatile solution that bridges the gap between computationally expensive simulations and rapid, reliable prediction models suitable for deployment in applications such as optimization and/or yield analyses [29], [30]. Surrogate models, also known as metamodels are approximate representations of the underlying systems, providing valuable insights into their behavior while significantly reducing the computational burden. By leveraging data obtained from a limited number of simulations or experiments, these models facilitate the exploration of vast design spaces and enable efficient optimization, uncertainty quantification, and sensitivity analysis. Thus, it is a significantly more efficient method to perform optimization management over data driven surrogate models most especially models based on artificial intelligence (AI) algorithms such as artificial neural networks [31], [32], [33], [34], [35], [36], [37], [38], [39] or deep learning algorithms [40], [41], [42], [43], [44], [45], [46], [47], [48], instead of EM solvers. The data-driven surrogate model is used by many researchers for many applications such as parameter tuning [49], [50], statistical analysis [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53] and multi objective design [54], [55], [56], [57], [58]. Some examples from the literature, for the application of AI based surrogate models are polynomial regression [59], Kriging interpolation [60], radial basis functions [61], support vector regression [62], and polynomial chaos expansion [63], [64], [65], [66], one of the commonly used techniques is artificial neural networks (ANNs) [31].

Herein, for having a high-performance broad band PAA for the millimeter band in a computational efficient manner, an AI based surrogate model assisted optimization approach is deployed via the use of EM solver-based training samples. First, the unit antenna and PAA design were carried out by means of a 3D EM simulation program. Then, a data set was created for PAA in line with the phase and amplitude information. In Section II, the novel ANN-based surrogate modeling and optimization processes of the 2 × 2 PAA are determined to obtain the desired combined output depending on the phase and amplitude variables. In Section III, experimental studies on optimized PAA design are indicated. The surrogate model is also used alongside a metaheuristic optimization algorithm to achieve the desired PAA design. Section IV explains the fabrication and measurement results. Finally, general information was given about the results of the study.

II. GENERATION ULTRA-WIDE MILLIMETRIC BAND PHASED ARRAY ANTENNA DESIGN

While designing the PAA, it was aimed to design an antenna that provides broadband and high antenna efficiency that can be used for many applications in the millimeter band. In this direction, a high-gain and very broadband antenna design has been realized by using a traditional patch antenna with circular polarity and a parasitic element using Rogers 4350B material. The most important design parameters while performing the PAA design are unit and combined gain efficiency and impedance compatibility of each unit element with the connector, operating bandwidth in the millimeter band and substrate selection and mechanical sensitivity. PAA was made from circular patches on the main and parasitic PCB with 4 outputs. Bandwidth and gain are increased thanks to parasitic patches. It also has a 50-ohm feed line and ground plane to get the outputs of each unit element through the connector. There is an air gap between both patches and this gap is optimized according to the resonance frequency of the circular patch on the main PCB. Both the main and parasitic PCBs were designed with RO4003 0.254mm. The steering of the main beam in different directions is achieved by feeding the excitation signals at the ports with different phases. Each patch element is fed by a supply line with a quarter wave transformer in between for impedance matching. The black box model is in Fig. 1 (a) and the flow chart of the proposed antenna design is given in Fig. 1 (b). First, the unit circular polarity patch antenna design was realized. As a result of the optimization, the main and parasitic element patch antenna dimensions and air gap distance were determined. The resulting dimensions are $G_1 = G_2 = 12$, $M_1 = P_1 = 2.8$, $S_1 = 0.4$, $S_2 = 0.6$, $L_1 = 1$, $L_2 = 1.524$, $L_3 = 2.25$, $W_1 = 0.14$, $W_2 = 0.31$, $W_3 = 0.56$, $A_1 = 0.735$ mm. The operation frequency of the K-band is between 26-35 GHz. The gain of the unit antenna is about 7 dBi and the return loss is better than −6 dB at the whole operation band. The unit antenna 3D model and S_{11} result are presented in Fig. 2 (a) and Fig. 2 (b).

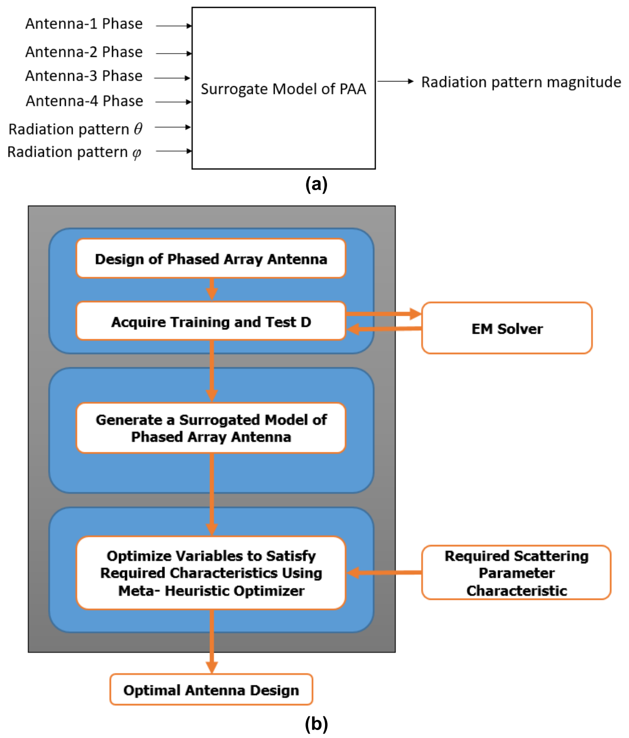

FIGURE 1. **(a) Black box representation, (b) Flow chart of the proposed antenna design.**

In the next stage, the PAA design by using the designed unit antenna element is done in a 2 × 2 configuration. The 3D model of PAA is in Fig. 2 (c). The working bandwidth was preserved as it was in the unit antenna. Here, it is worth mentioning that the patch antenna, slot dimensions, air distance and feed line widths are the same as the unit antenna. The return loss of each port of the PAA antenna is shown in Fig. 2 (d). The distance from the center to center of each patch antennas is $D_1 = 11$ mm. The distance between the centers of the patch antenna corresponds to about half of the wavelength of the center frequency (30.5 GHz). PAA simulation, time domain finite integration was applied in CST with a transient solvent using the method. In addition, the radiation patterns of the antenna are shown in Fig. 2(e-f) with randomly selected values in the range of phase angles determined in the data set, both on the azimuth and elevation axis.

The PAA structure consists of a 2 × 2 PAA structure and is intended to be used as a feeder antenna for many applications such as the feeding of reflector antennas, radar systems, and radio link systems for 5G applications. The studied PAA is modelled in a 3D EM simulation program (CST MWS) designed for 5G and radar applications in millimeter band and ultra wide range as shown in Fig. 2. Here it should be emphasized that the determination of the optimal phase and magnitude value for this PAA is a complex and time-consuming procedure due to the nature of 3D EM simulators which makes the whole design process a computationally expensive design problem [28]. Thus, although it is a multi-dimension optimization problem, it is not a feasible or computationally efficient procedure to be solved via the traditional direct full wave EM simulator assisted optimization search protocols.

TABLE 1. **Data set design variables and limits.**

Variable	*Min.*	*Max.*	*Sample Step*
Antenna-1 Phase	0	315	45
Antenna-2 Phase	0	315	45
Antenna-3 Phase	0	315	45
Antenna-4 Phase	0	315	45
Theta Angle	-90	90	1
Phi Angle	0	90	90

Herein, for solving this computationally expensive optimization problem an artificial Intelligence base surrogate model assisted optimization procedure is taking under consideration. Application of surrogate models for the design and optimization of high-performance microwave stages is an efficient method that being used by many researchers for different types of designs with promising results [56]. The proposed surrogate model will create a mapping between the input (input phase of each unit antenna) and the radiation characteristic of the PAA design in Fig. 2(e) and Fig. 2(f). For this mean in Table 1, the design variable of surrogate model is presented. The training and validation data sets required for creating surrogate model will be generated based on the given lower and upper limits in Table 1. For this study the amplitude value of each antenna feed is taken as unity. Each unit antenna can take a total of 8 different angles between 0 and 315 degrees with 45-degree phase difference intervals. A total of 4096 (8 × 8 × 8 × 8) training data were obtained. Since the output of each combined data was analysed at all theta angles and the theta angle range was taken as 1 degree, a data set consisting of 741.376 (4096 × 181) lines was created for the 26 GHz frequency. Within the scope of this study, a data set was created for a single frequency first.

The 3D EM simulation studies were performed using the Finite Integration Technique, the selected PAA design has a mesh size of approximately 1,366,767 cells per wavelength & max model box edge = 20, Fraction of the maximum cell near to model=20, using a simulation setup with following specs: Intel(R) Core(TM) i7-6700K CPU @ 4.00GHz, with 32 GB of installed memory. The simulation time was around 17 minutes. To obtain the combined pattern of the 4-element antenna design with the desired input phase angles, the combined results feature of the EM simulation program CST is used. Thus, the desired phase values were given to each port in equal amplitude (here taken as unity) and a data set was created. Thanks to this feature of CST, the far-field results of each combined pattern were obtained around 2 minutes for generating the samples for data sets.

III. DATA DRIVEN SURROGATE MODEL ASSISTED DESIGN OPTIMIZATION

As can be observed, from Fig. 2 (e-f) and antenna array theory, with variation of phase of each unit element the

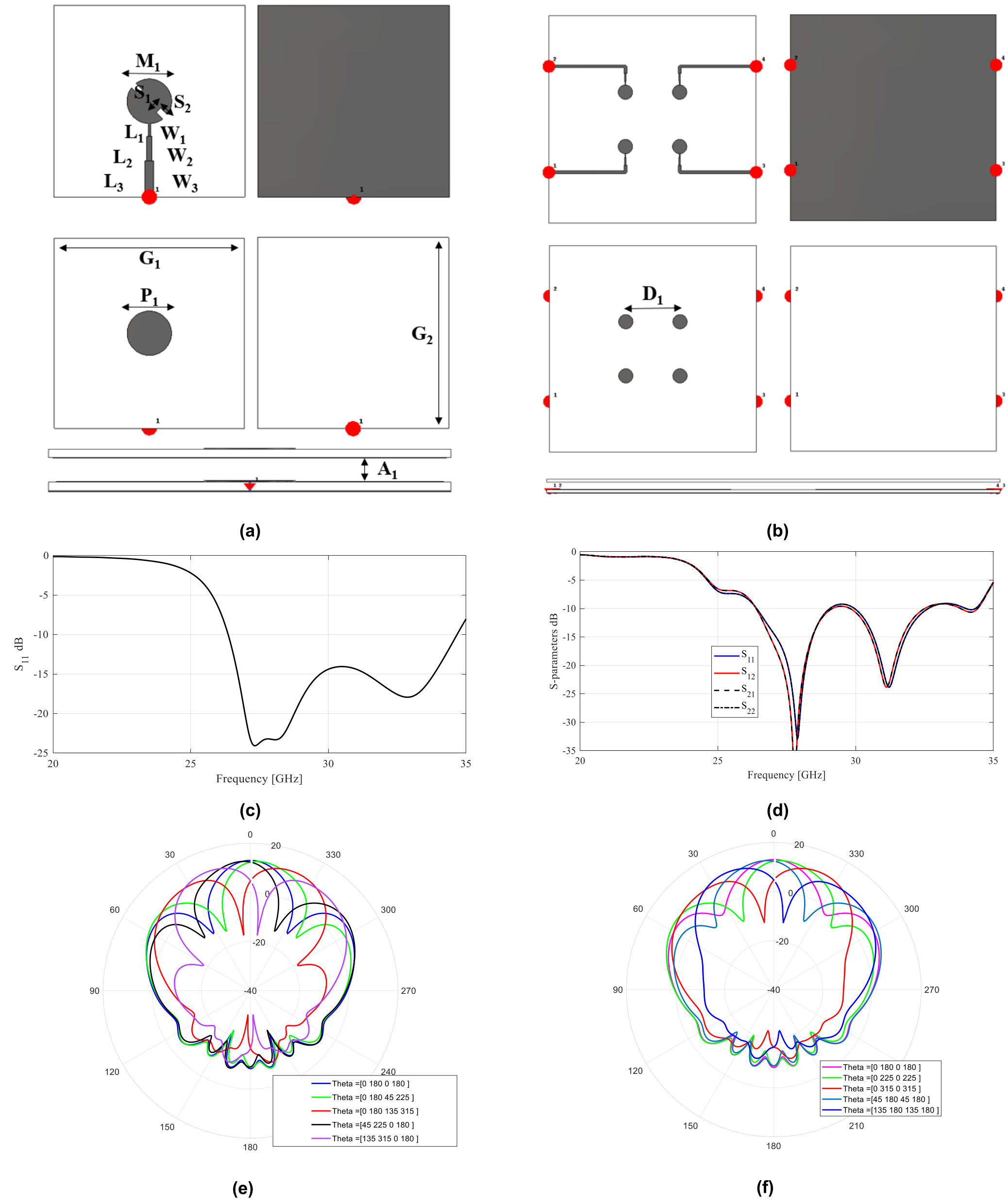

FIGURE 2. Schematic of (a) unit antenna, (b) PAA design; S_{11} characteristic of (c) unit antenna, (d) PAA design; Radiation pattern with randomly selected phase angle for (e) azimuth, (f) elevation plane.

TABLE 2. Surrogate model and their performance measures (MAE±standard deviation) for 10 different runs.

Design Parameter	Hyper-parameters	MAE		Average Training Time [Mniutes]
		Average ± std	Best of 10 runs	
MLP	Layer size 2, Neuron size 20-30, Bayesian regularization method	1.34±0.82	0.7082	4.8
EL	LSBoost, Learning rate 0.18, Min Leaf size 24	1.79±0.04	1.7531	1.9
CNN	Layer size 4, Neuron size 64-128-256-512, optimizer adam, batch normalization 1000, epoch 1500	0.87±0.6	0.6296	9.8
M2LP	Depth size 2, Initial neuron size 32, optimizer adam, batch normalization 1000, epoch 1000	0.32±0.01	0.3102	6.4

radiation pattern is changed. In this section by using the data sets generated in the previous section a data driven surrogate model of proposed PAA is generated via a different type of AI algorithm. For this mean, series of traditional and state

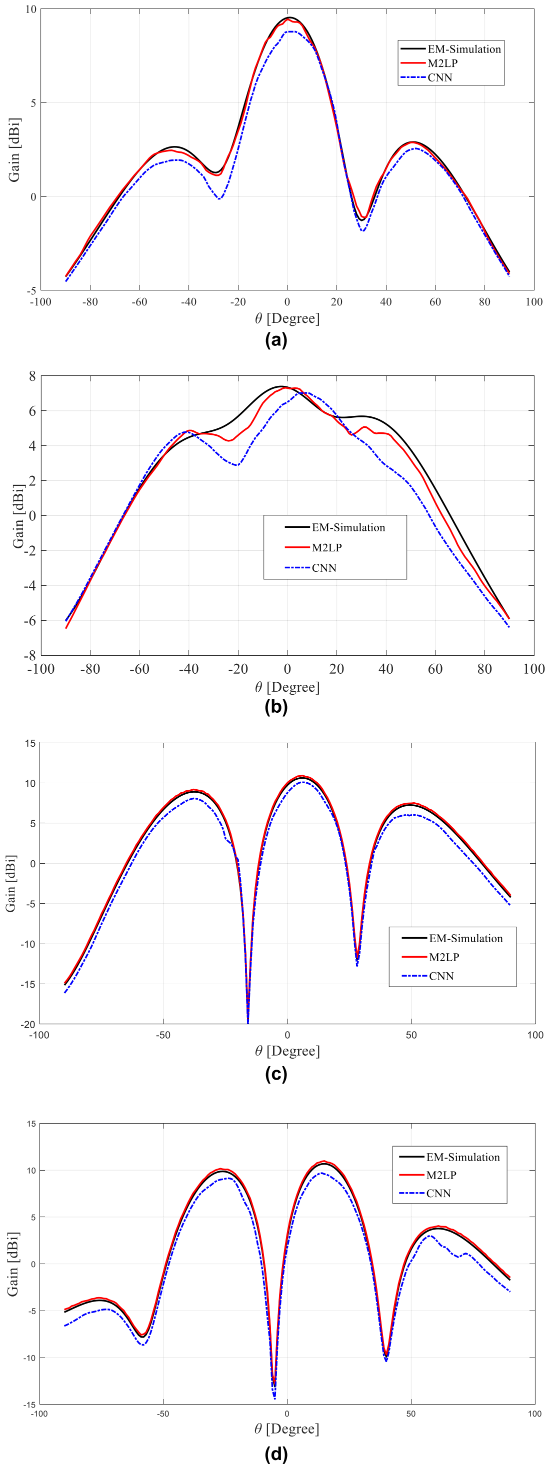

FIGURE 3. Radiation characteristics of (a) Case I [225°, 135°, 90°, 0°], (b) Case II [315°, 180°, 0°, 315°], (c) Case III [30°, 0°,180°, 244°], (d) Case IV [147°, 0°, 180°, 296°] designs; EM-simulated versus M2LP and CNN predicted @ $\theta = 0°$, 26 GHz.

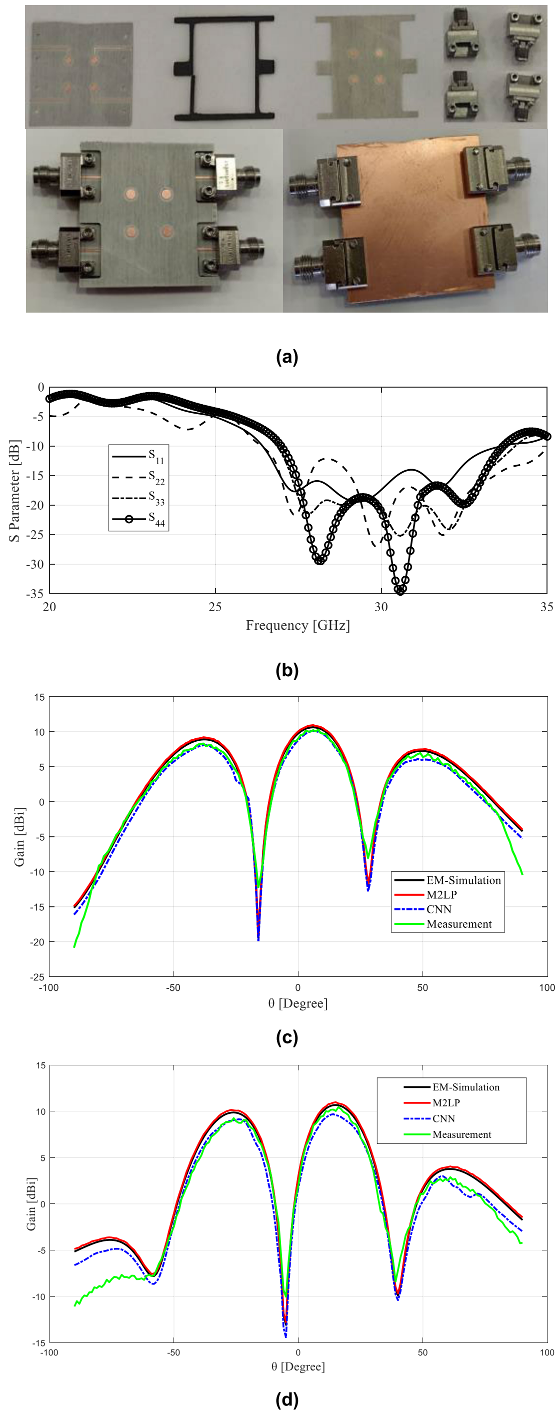

FIGURE 4. (a) The prototype 2 × 2 PAA; (b) measured S-parameter results; measured radiation pattern versus surrogate models' predictions @ 26 GHz for (c) Case III [30°, 0°, 180°, 244°], (d) Case IV [147°, 0°, 180°, 296°].

of the art algorithms Multi-layer Perceptron with single and two hidden layers, Ensemble Learning (EL), a deep learning-based AI network Convolutional Neural Network (CNN) and Modified Multi-layer Perceptron (M2LP) [43] with depth size of one and two are taken into considerations. A crucial design step in surrogate modeling is tuning of surrogate model hyper-parameters [67] that can significantly affect the prediction accuracy of models. In this work, these parameters are determined via the Bayesian optimization approach [68]. For each of the surrogate models based on a K-fold cross validation with K=3 where the whole data is shuffled and divided into two equal partitions is created. In Table 2, the Mean Absolute Error (MAE) metric is used to evaluate generalization capabilities of these surrogates between the predicted radiation gain values at given inputs vs. the simulated value from CST using K-fold validation. As can be seen from Table 2, M2LP model achieves highest accuracy and precision performance with respect to both average and minimum obtained MAE metrics. For illustration of these performance responses, the radiation characteristic belonging to CST simulated results, M2LP prediction and CNN for three design cases is presented in Fig. 3.

It is worth noting that while investigating optimization algorithms for the purpose of optimizing microwave antenna designs is a challenging and valuable research area, the present study does not focus on the speed or convergence rate of these methods. The primary objective of this study is to introduce a computationally efficient data-driven-surrogate modeling technique. The proposed approach is aimed at enhancing the overall design optimization process by minimizing the convergence time of the optimization algorithms in relation to the total computational time required for the entire process using an AI based regression approach. Here for the studied optimization problem, the usage of any techniques at least would require at least 1500-2000 function evaluations (such as the Trust-Region algorithm or, Particle Swarm Optimization). This means that the optimization process would requires almost 425 hours (1500 $\times$ 17 (total number of function evaluation $\times$ average simulation time of each antenna design in minutes)) using the direct EM optimization approach for each and every aimed design case. Let us assumes that the designer would requires two different design cases, thus for these two different cases the total required computational time using the traditional approach would be around 1275 hours (3 $\times$ 425).

In the proposed approach although the generation of 4096 samples is a heavy computational cost, which is the main cost in surrogate models known as initialization cost, the total time required for creating a model would be around 136.5 hours (4096 $\times$ 2 [minutes]) even by using the combined results feature of CST. However, once the surrogate model is trained the simulation time required to predict the radiation characteristic for the given inputs response time of surrogate model is less than 0. 1 seconds. Thus, the prediction of thousands of different design cases or solution candidates would require a computational time of less than two minutes which is less than a single simulation run of the traditional approach in the EM simulation model. To briefly summarize the acceleration of the design optimization process for the studied problem, the following example can be assumed. Let us assume that three PAA designs are aimed to achieve with different radiation characteristics. In the case of optimization of these designs at least 1500 function evaluations for each design (4500 function evaluations in total) are required for having a global local solution. In case of using traditional direct EM simulation tool approach this process would requires approximately 1275 hours (3 $\times$ 425 [hours]), while in case of using the proposed data-driven surrogate modeling approach, the total required time is no more than 138 Hours (including, the initialization cost of 136.5 hours + the time required for training the surrogate models less than 1 hour + 4500 of function evaluations for optimization process which is approximately less than 8 minutes [4500 $\times$ 0.1 [seconds]]) in total. Thus, the overall computational cost for optimization of three cases of studied PAA is reduced by almost 90.0%. It is worth noting that there are alternative data-driven surrogate techniques, such as inverse modeling [69] that can be employed to achieve designs with superior performance. Nevertheless, it is important to acknowledge that these methodologies do have certain limitations. One such drawback is the restricted Design of Freedom (DOF) for problem variables. This means that a given desired performance outcome may have multiple potential solutions, sometimes even dozens, resulting in non-uniqueness difficulties. Specifically, the model's ability to generate distinct responses may be compromised as a result of its inability to appropriately alter the weighting coefficients for identical inputs with varying outcomes. As a result, the designer must eliminate or assign fixed values to certain design variables in order to decrease the degrees of freedom and performance of the achievable ideal design. The direct modeling approach remains unaffected by the aforementioned challenges related to uniqueness. However, a drawback of forward-modeling-based approaches is the requirement for frequently time-consuming model optimization in order to ascertain the ideal solution for the desired performance outcome. However, in cases when the forward model is computationally inexpensive, such as in this study, the aforementioned issue has been successfully mitigated, resulting in a negligible cost for design optimization. Given that each function evaluation anticipated by the model requires less than one millisecond, it is evident that an optimization process consisting of 10,000 objective function calls would be completed in less than one minute. This duration is equivalent to the time required for a single EM analysis of the individual design.

IV. EXPERIMENTAL RESULTS

In this section, to demonstrate the validation and applicability of the proposed data-driven surrogate modeling approach experimental results of an optimally designed PAA using M2LP is studied. In Fig. 4, the prototype PAA antenna alongside of measured and predicted radiation characteristic of the antenna is presented. The production and measurement of the antenna was carried out in the NETA Elektronic Inc. laboratory. A network analyzer was used for all measurements. The Rohde-Schwarz ZNB is a two-port device that can measure up to 40 GHz. First of all, the return losses (S_{11}) of the antenna were measured with a network analyzer and compared with the design results. A 4 $\times$ 50 ohm 2.92 mm K connector is used as the connector. The comparative S_{11} results of the simulation and measurement are given in Fig. 4 (b). For justification of the prediction accuracy of the surrogate model compared to experimental results, for three cases with varying input phases (these values are not included

TABLE 3. Antenna performance comparison table.

	f [GHz]	Array Size	BW	Gain [dBi]	Size [λ_0]	Scan Range	Parasitic Element
This Work*	26-35	2x2	30%	13	4.27x4.27	60°	Used
[10]#	27.55-28.59	1x4	3%	10	0.34x1.36	50°	Not Used
[11]#	34-36	16x16	5%	28.6	N/A	45°	Not Used
[12]*	30-40	8x8	28%	25	3.84x6.56	30°	Not Used
[20]#	16-17	1x8	11%	11	3.68x7.3	75°	Not Used
[22]#	24-30	5x5	22%	18	N/A	50°	Used
[64]#	24-30	2x8	22%	12.7	5.31x0.756x0.121	35°	Not Used
[70]*	24-30	19x16	22%	14.5	5.3x4.5x0.54	38°	Not Used
[71]#	38	91x91	2.63%	23	20x20	30°	Not Used

Experimental Results, # Simulation Results

in the generated data in Table 1) the measured, simulated and predicted radiation characteristics are shown in Fig. 4 (c-d), the radiation characteristic measurements were measured at far-field distance under laboratory conditions. As it can be observed form the results the proposed approach is not only a computationally efficient method for design optimization or repetitively analyses, but also has a high accuracy and precision rates. As for a further analysis on the studied PAA design a detailed performance comparison of the prototyped PAA with its counterpart design in the literature are shown in Table 3.

V. CONCLUSION

In this paper, for having a high-performance broad band PAA for millimeter band in a computational efficient manner, an AI based surrogate model assisted optimization approach is deployed via the use of EM solver-based training samples. First, PAA design was carried out by means of a 3D EM simulation program. Then, a data set was created for each unit antenna in line with the phase and amplitude information. Then series of state-of-the-art surrogate modeling algorithms are deployed to create a surrogate model of the 2×2 PAA design for the prediction of radiation pattern characteristic with respect to the input phase values of each array element. In this work, the key achievement lies in the drastic reduction in computational time. This time saving is exemplified by a 90.0% decrease in time for the optimization of three PAA designs [1275 hours vs. 138 Hours]. This surrogate modeling approach, despite the initial heavy computational cost, demonstrated immense efficiency in design optimization and/or repetitive analyses. Experimental results further showcased the effectiveness and accuracy of this approach. The comparison of the surrogate model predictions with measured results depicted high precision rates, corroborating the model's capability. Moreover, comparisons with existing literature affirmed the success of the proposed PAA design. This study thus indicates that the integration of AI and surrogate modelling in antenna design is a potent solution, streamlining the design process, enhancing computational efficiency, and ensuring high-accuracy results. This approach offers promising avenues for further exploration in computational electromagnetics most especially in simulation expensive problems with complex designs. In feature work authors aim to further improve the computational efficiency of this approach based on a reduction of initialization cost using novel sampling approaches to achieve similar surrogate performance with smaller training data sets. In this endeavor it is worth mentioning that reducing the number of training data would reduce the accuracy of the model however this reduction can be minimized with more strategically sampling approaches that could provide more information on the problem domain even with lesser sample sizes.

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