Conference Paper

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Machine Learning-Assisted Optimization of a Metasurface-Based Directly Modulating Antenna

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***Abstract*—A directly modulating antenna using metasurfaces is optimized using the surrogate model assisted differential evolution for antenna synthesis (SADEA) method and simulated. Metasurface modulation holds promise as an energy efficiency transmitter technology, but suffers from modulation distortion and many differing parameters, making achieving good designs difficult. The algorithm used here, SADEA, obtained a design that shows improvement over conventional design techniques, producing amplitude variation of 1.8 dB over 360^o and an average efficiency of 65%, up from 50% obtained by the standard model.**

I. Introduction

Direct modulation, where a radio frequency (RF) carrier wave is modulated at transmit power, has been proposed as a form of energy efficient transmitter [1]. Conventional transmitters require amplification of a modulated signal, placing limits on the linearity of the power amplifier (PA) and so reducing the transmitter efficiency, often to below 30% [2]. Reconfigurable metasurfaces have been suggested as a mechanism for performing direct modulation, as tuning a metasurface's response produces a phase change in the transmitted or reflected signal [1]. Techniques have also been demonstrated for producing more complex quadrature modulation [3], [4].

However, both transmissive and reflective metasurface phase modulation techniques suffer from an unwanted variation in magnitude with phase. As the metasurface response is effectively a filter, there is significant variation at the carrier frequency as the filter response tunes across its bandwidth. The effect is worsened by losses in resistive parts of the metasurface, in particular the tuning elements. This affects the quality of modulation, introducing distortion to the intended constellations.

Machine learning-assisted optimization methods are attracting a lot of interest for the expedited design of contemporary antennas in recent times [5]. To address the challenges above, this paper utilizes the surrogate model assisted differential evolution for antenna synthesis (SADEA) method to minimize the magnitude variation of a directly modulating antenna using transmissive metasurfaces. SADEA is a purpose-built machine learning-assisted global optimization method for antenna design [6]. When compared to standard global optimization methods for antenna design, SADEA offers up to 20 times speed improvement and obtains design solutions of enhanced quality [7]. Hence, it is used in this work.

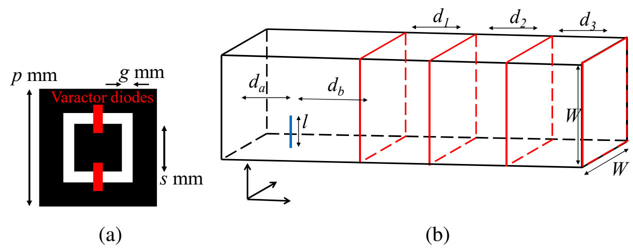


Fig. 1. (a) Unit cell of metasurface, (b) Directly modulating antenna

II. Directly modulating antenna

The general design of the modulating unit was first introduced in [1], and is shown in detail in Fig. 1. The working principle is that a 1.8 GHz carrier wave is introduced into a cavity by a monopole of length l. It illuminates a series of reconfigurable metasurfaces, which acts as a bandpass filter. By tuning the response continuously over its range, the phase of the carrier wave is altered, allowing information to be modulated onto it, for example with phase shift keying.

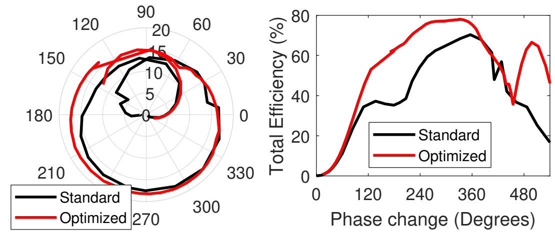
The metasurface unit cell is shown in Fig. 1a, with two varactor diodes arranged in line with the expected E-field from the transmitter in a conventional tuneable bandpass loop configuration. The diodes are modelled as a series RLC circuit with resistance 0.7 Ω, inductance 0.5 nH and variable capacitance between 0.8 pF and 1.5 pF. Each metasurface consists of a 5x5 grid of unit cells, and put on a substrate of Rogers RO3003 with a relative permittivity of 3 and a loss tangent of 0.001. Bias lines are placed on the back of each surface to allow voltages to reach each diode, with thickness b_t and offset b_o from the cavity wall. Four layers of metasurface are used to ensure 360^o phase change is available, and they are integrated into an antenna cavity as shown in Fig. 1b.

The monopole feed is placed at a distance of d_a from the back of the cavity. Each surface is then spaced from each other by distances of d_1, d_2 and d_3, respectively. The width of the cavity W is determined by $5p$ where p is the periodicity of the unit cell.

The large number of interacting parameters makes manual optimization of the structure difficult. To allow machine optimization, the whole capacitive tuning range is represented by

TABLE I
DESIGN PARAMETERS FOR THE ANTENNA (ALL SIZES IN mm)

Parameter	Lower Bound	Upper Bound	Standard	SADEA-Optimized
p	15.00	23.00	23.00	22.60
g	0.25	1.30	1.00	0.28
s	20.00	50.00	17.00	20.54
l	15.00	50.00	42.00	38.63
d_1	40.00	80.00	57.00	77.00
d_2	40.00	80.00	57.00	65.00
d_3	40.00	80.00	57.00	63.00
d_a	40.00	70.00	57.00	66.00
d_b	20.00	50.00	57.00	46.84
b_t	0.50	5.00	1.00	3.32
b_o	1.00	20.00	5.00	18.27



(a) (b)

Fig. 2. (a) Normalised E-field magnitude and phase at boresight of antennas at 1.8 GHz, with changing capacitance (b) Total efficiency of modulating antennas at 1.8 GHz against phase change produced

four evenly spaced samples from across the range: 0.88 pF, 0.95 pF, 1.02 pF and 1.09 pF.

III. SADEA-BASED OPTIMIZATION

SADEA works by harmonizing machine learning and evolutionary computation techniques in a unified optimization framework for improved efficiency and optimization quality [6]. To carry out global optimization, SADEA employs differential evolution, and it uses Gaussian process-based surrogate modelling to predict the performances of candidate antenna designs in the optimization process. The harmonious coworking of global optimization and surrogate modelling in SADEA is achieved via surrogate model-aware evolutionary search framework [8].

In this work, SADEA is implemented in MATLAB [9]; a population size of 50 and a computing budget of 200 full-wave EM simulations for each capacitive state of the modulating antenna have been used. Other settings are the default recommended in [6]. The design parameters and their search ranges considered for the optimization of the modulating antenna are shown in Table I. To ensure geometric congruity during the optimization, the geometric constraints used are $b_t/2 < b_o$ and $s + g < p$. The optimization goal is to minimize the difference between the magnitudes of the E-field components at the antenna's boresight, at an operating frequency of 1.8 GHz for the capacitive states, subject to a return loss lower than -6 dB and a total radiation efficiency better than 65%.

IV. RESULTS AND DISCUSSION

After 144 full-wave EM simulations for each capacitive state considered, SADEA converged to obtain the optimized design shown in Table I. For comparison, a standard design was manually produced with conventional design rules, such as spacing all surface layers $\lambda/4$ apart, and these dimensions are also shown in Table I. Both designs were then simulated over the range of capacitances available to the diode, and their simulated results are shown in Fig. 2.

The optimized antenna's E-field at boresight shows a significant reduction in amplitude variation with phase at 1.8 GHz, compared with the standard antenna (Fig. 2a). As such the modulation produced will be less distorted when the optimized antenna is used. For example, the optimized antenna's QPSK constellation has points 82%, 92% and 94% of the maximum amplitude, while the standard model has a more distorted constellation with points at 75%, 84% and 93% of the maximum value. Around 360^o phase change, the optimized model has 1.8 dB variation, a significant improvement over the 3.1dB variation of the standard model.

Further, the efficiency of the optimized antenna is also greater than that of the standard model. The average efficiency over 360^o phase change has increased from 50% to 65%. As such, the SADEA-based optimization enables improvement of complex directly modulating antennas well beyond the performance of standard design rules.

V. CONCLUSIONS

A directly modulating antenna using metasurfaces has been optimized using SADEA. The optimized antenna showed an improved constellation over a conventionally designed standard antenna, reducing a 3.1 dB variation in amplitude over 360^o to 1.8 dB. The average efficiency over 360^o also improved from 50% to 65%. This demonstrates the utility of the algorithm in optimizing complex directly modulating structures. Future work will explore algorithmic co-design of the modulating antenna and the physical layer waveform.

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