Customized Inverse Design of Metamaterial Absorber Based on Target-Driven Deep Learning Method

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ABSTRACT Metamaterials (MMs) have already achieved wide applications in academia and industry. The traditional design approach for MMs highly relies on full-wave numerical simulations and trial-and-error methods. It is time-consuming and laborious to obtain the optimal design parameters. Recently, extensive researches have shown advantages and superiority of the deep learning method in solving non-intuitive problem. Several attempts have been made to demonstrate Artificial Intelligence (AI) usage in the electromagnetic field. In this article, a target-driven method empowered by deep learning to realize customized metamaterial absorber (MMA) design has been proposed and demonstrated numerically. Unlike previous deep-learning-based design methods for MMs which directly use the spectrum response to generate the MMA’s design parameters, this method takes the frequency domain response of the absorber as the intermediary bridge to establish the mapping between MMAs geometry/material parameters and customized figure-of-merits. The proposed design framework greatly simplified the design process of MMAs, and it can also be generalized to realize automatic inverse design for other kinds of metasurfaces.

INDEX TERMS Metamaterials, absorber, inverse design, deep learning, neural network, resistive films.

I. INTRODUCTION Metamaterials (MMs) are artificial engineering media which consist of periodic or nonperiodic geometric arrays with sub-wavelength unit cells. To date, MMs have demonstrated their unprecedented capability in manipulating the properties of electromagnetic (EM) waves including amplitude, phase, polarization and etc. Their exotic properties mainly arise from geometry details and constituting material of the unit cell. The specific feature of MMs leads to many novel applications such as perfect metamaterial absorber (MMA) [1], metalens [2], [3], coding metasurface [4], holographic imaging [5] and EM shielding [6]–[9]. Among all these researches, MMAs have attached more and more attention with applications ranging from microwave to optic spectrum. Various MMAs have achieved narrowband [1], wideband [10]–[12], or multiband absorption [13]–[15]. These novel devices have been widely used in the areas of bolometers [16], radar cross section reduction [17], imaging devices [18], EM compatibility [19], sensing [20]–[22], and EM interference shielding [23].

According to different realization mechanisms, MMAs can be categorized as resonant type and broadband type. The resonant absorbers rely on interacting with the incident radiation in a resonant way at a specific frequency. Normally it has a simple structure with limited absorption band which is easy to design using equivalent circuit theory. The broadband absorbers rely on using frequency-independent materials that...
show absorptivity over a large bandwidth. Commonly it is polarization-insensitive, incident-insensitive, but the pattern of the unit cell is much more complex to design.

In the recent studies, some researchers have proposed novel MMA based on resistive films, this type of MMA are lightweight, ultrathin, and easy to fabricate. They are mainly composed of three layers which can be described as “resistive film-dielectric-resistive film”. Different kinds of resistive films, such as ITO, graphene and etc, have been used as the lossy layer of MMAs. Using the industrial process of excimer laser micromachining, photolithography, or etching process, the resistive film can be patterned to different geometries such as crosses [10], triangles [24], rings [25], and these unique unit cells pattern defines their novel properties to realize broadband or multiband absorber.

So far, the traditional design approach for MMA still relies on empirical reasoning or trial-and-error method [26]–[29]. The design process was also assisted by optimization algorithms such as topology optimization [30], genetic algorithm [31], gradient-based algorithm [32]. These algorithms contain iterative searching steps and rely on full-wave numerical simulations in each step to produce intermediate results that avail optimization for the searching strategy. However, the random-search nature of such stochastic algorithms is restricting their capacity on the complex design problems. Hence, a more simple and efficient manner for the design of MMA with customized figure-of-merits is still highly desirable.

In the past few years, deep learning has shown advantages in a wide range of applications in different areas such as computer vision, natural language processing, speech recognition, and face recognition [33]–[35]. Deep neural network (DNN) based approaches have proved great expectations in solving non-intuitive problems needing identifications and optimizations, it provides a promising solution to solve the trial-and-error problem with its excellent generalization ability [36]–[38]. The basic structure of the DNN is illustrated in Fig. 2. Since DNN contains several hidden layers that consist of multiple neurons as a huge multi-level graph model, it can be utilized to represent extremely complex functions according to the universal approximation theorem [39]–[41]. Based on the extraordinary properties of DNN, there is a possibility to uncover the hidden relation between MMs and their EM responses.

A series of early works have exhibited the potential of AI-based methods in solving EM problems. Tao Shan et al. reported a deep convolutional neural network to design the coding programmable metasurface [42]. Sensong An et al. proposed a novel conditional generative network which can generate the metasurface designs based on different performance requirements. He also introduced a DNN approach that significantly improved the speed and accuracy for designing metasurface-based devices [43], [44]. Liu et al. introduced DNN to the inverse design of nanophotonic structures and constructed a DNN model which takes the EM response as input and generate the geometric structure parameters as output [36]. Nadell et al. used deep learning for accelerated all-dielectric metasurface design assisted with a fast forward dictionary search method [45]. Compared with the trial-and-error method, those deep-learning-based methods are simpler and efficient since the well-trained neural network model can automatically output the design parameters of the target in a few seconds. However, those methods have a common feature that the transmission or reflection response, which consists of many sampling points, is set as the input of the design model to inverse design the MM devices. Nevertheless, in the actual design process, the designer will only have the specific performance indexes instead of a precise S-parameters response spectrum as long as the performance of the response spectrum meets their requirements. Hence the inverse design of the MMAs according to the customized performance index has been an open question.

In this article, the target-driven inverse design method based on deep learning algorithm is proposed which can effectively obtain geometry parameters and constitution material parameters of MMAs with on demand figure-of-merits. Namely all the design parameters of the MMA are associated with the performance index of its absorptivity spectrum through a deep-learning-based inverse design model. Once the training process of the DNN models is accomplished, the DNN model can automatically generate the design parameters of the target MMA with absorptivity that meets the input customized performance index, which consists of the upper and lower limit frequency and the slope at the upper and lower limit frequency. The test result demonstrates that our model can reach good results with an average accuracy of 93.5% in the testing datasets.

II. METHOD

Without loss of generality, the target-driven deep learning method has been applied to the design of an MMA unit cell which is depicted in Fig. 1. This unit cell composed of three layers: on the top is the patterned resistive film with a surface resistance of $r \Omega/\text{sq}$ which printed on the 0.175mm thick Polyethylene Terephthalate (PET) sheets ($\varepsilon_r = 3.2$ and $\tan\delta = 0.003$), in the middle is the polymethacrylimide (PMI) foam, and the bottom layer is a 0.175mm thick PMI sheet covered with the resistive film. The period ($p$) of the unit cell is 12mm, the thickness of the foam layer is $t_d$. The pattern on the top resistive film is a Jerusalem cross shape slot which can be characterized with parameters $[l_1, l_2, w_1, w_2]$, the resistive film on the bottom act as a nearly perfect reflection layer which has a surface resistance of $10\Omega/\text{sq}$. As mentioned earlier, the geometry structure and the material characteristic are critical to the performance of the MMA, thus the design for an MMA with designated pattern rely on the optimization of parameters $[w_1, l_1, w_2, l_2, t_d, r]$.

The general schematic of the proposed customized inverse design method is depicted in Fig. 3, the flowchart of the proposed approach consists of design process and training process. The design process is implemented with the feature transformer neural network (FTNN) and the generator neural
The FTNN can generate the target absorptivity spectrum according to the customized input performance index of the target absorber. The GNN will take the output of the FTNN as inputs, then generate the design parameters of the target absorber according to the target absorptivity spectrum. In the training process of the inverse model, a predictor neural network (PNN) is introduced. The PNN can predict the absorptivity of the MMA according to the input design parameters with high speed and accuracy.

To design the target MMA according to the customized figure-of-merits of the target spectrum, the mapping between target MMAs’ design parameters and customized performance index should be established, in the meantime, the absorptivity spectrum of the absorber must satisfy the characteristics of the target spectrum. In order to satisfy all these requirements, the spectrum response sets up a bridge to map customized performance index with design parameters. As described above, the customized performance index is associated with the target spectrum by the FTNN, meanwhile, the GNN and the PNN link the design parameters with the designed spectrum. Three neural network models are trained and connected, depicted in the orange area of Fig.3. The consistency between the target spectrum and the designed spectrum will gradually improve along with the training process. When the target spectrum is highly consistent with the designed spectrum, the mapping between customized performance index and design parameters can be considered to be settled. The detail of realizing forward prediction and inverse design will be introduced in the next two subsections.

### A. FORWARD PREDICTION

As demonstrated in Fig.3, in the training process, the difference between the designed spectrum and the target spectrum needs to be calculated immediately. Since the traditional simulation way to obtain the spectrum of a specific absorber is time-consuming and laborious, a PNN is constructed to replace the full-wave numerical simulation in order to rapidly forecast the spectrum.

| Layers          | Dimensions | Normalization | Activation Function |
|-----------------|------------|---------------|---------------------|
| Input           | 6x1        | \             | \                   |
| Hidden layer 1  | 16x1       | Batch Norm    | LeakyReLU           |
| Hidden layer 2  | 64x1       | Batch Norm    | LeakyReLU           |
| Hidden layer 3  | 128x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 4  | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 5  | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 6  | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 7  | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 8  | 128x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 9  | 64x1       | Batch Norm    | LeakyReLU           |
| Output          | 33x1       | \             | \                   |

The configuration details of the PNN are shown in Table 1. The PNN is composed of an input layer, nine hidden layers, and an output layer. The input of the PNN is a vector consisted of geometry parameters and the material parameters, and the output of the PNN is discrete absorptivity value sampled at 33 specific frequencies. Theoretically, the fitting performance of the neural network is proportional to the numbers of hidden layers and neurons, but when the network becomes deeper, a series of problems, such as gradient exploding [46] or gradient vanishing [47], will also arise which may cause non-convergence problems or invalid calculations. It will lead to a waste of computing resources and also increase the training time. As illustrated in Fig.4, different numbers of hidden layers have been tried in the experiments, when the number of hidden layers is nine, the model achieves the best
FIGURE 3. In the design process, the FTNN take the customized performance index as its input and output the target spectrum, which will be sent to the GNN, the GNN then generate the design parameters. In the training process, the predictor will take the design parameters as its input and generate the predicted spectrum as output. The predicted spectrum of the current design will be compared to the target absorptivity which output by the FTNN, the difference between them will be calculated and backpropagation as the loss.

FIGURE 4. The corresponding MSE of different number of hidden layers.

In order to accelerate the training process, batch normalization has been added to the neural network, which can avoid gradient vanishing problems and increase the generalization ability of the neural network [48]. It should be noted that the activation function (if used) in this model is LeakyReLU.

B. INVERSE DESIGN

As explained earlier, the performance index for the target absorber will be assigned by the designer to guide the design process. However, directly mapping the performance index to the design parameters can not guarantee the absorber meets the requirement. Therefore, to ensure the mapping between performance index and design parameters is accurate, the spectrum is used as an intermediary.

TABLE 2. Details of FTNN.

| Layer       | Dimensions | Normalization | Activation Function |
|-------------|------------|---------------|--------------------|
| Input       | 5x1        | \             | \                  |
| Hidden layer 1 | 16x1       | Batch Norm   | LeakyReLU          |
| Hidden layer 2 | 64x1       | Batch Norm   | LeakyReLU          |
| Hidden layer 3 | 128x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 4 | 256x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 5 | 256x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 6 | 256x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 7 | 256x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 8 | 128x1      | Batch Norm   | LeakyReLU          |
| Hidden layer 9 | 64x1       | Batch Norm   | LeakyReLU          |
| Output      | 33x1       | \             | \                  |

The FTNN is used to convert the input performance index into the desired target spectrum. The detailed structure of the FTNN is shown in Table 2. For the MMA performance, the designer’s primary concern is the frequency band and the absorbing rate. Thus the input of the FTNN consists of 5 elements, including upper and lower limit frequency of the absorbing band at the specific absorbing rate, the slope at the upper and lower limit frequency, bandwidth of the absorbing band. The output of the FTNN is the target spectrum that meets all of these input conditions. It is worth noting that although the upper/lower limit frequencies along with absorption rate are already enough for characterize the performance of an absorber, but it is not sufficient to generate a unique mapping between performance index and the target spectrum. This awkward circumstance can be illustrated in Fig. 5.

As it is shown, two completely different responses have the
same absorbing feature at 90% absorbing rate, but the neural networks can not distinguish their difference, which will lead to the non-convergence problem in the neural network model. To alleviate this problem, the slopes at upper and lower limit frequency of the absorption band have been introduced to ensure the uniqueness for the mapping between the customized performance index and the target spectrum. The slope at certain frequency is defined as:

$$S_n = \frac{A_{n+1} - A_{n-1}}{D \times 2}$$

(1)

where the $S_n$ represents the slope at the nth sample point, $A_{n+1}$ and $A_{n-1}$ represent the absorptivity of the two sample points before and after the nth sample point, and $D$ represents the sample interval.

**TABLE 3.** Details of GNN.

| Layer          | Dimensions | Normalization | Activation Function |
|----------------|------------|---------------|---------------------|
| Input          | 33x1       |               |                     |
| Hidden layer 1 | 64x1       | Batch Norm    | LeakyReLU           |
| Hidden layer 2 | 128x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 3 | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 4 | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 5 | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 6 | 256x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 7 | 128x1      | Batch Norm    | LeakyReLU           |
| Hidden layer 8 | 64x1       | Batch Norm    | LeakyReLU           |
| Hidden layer 9 | 16x1       | Batch Norm    | LeakyReLU           |
| Output         | 6x1        |               |                     |

The detailed architecture of the GNN is shown in Table 3. The GNN establishes the mapping between the target spectrum and the design parameters. The inverse design model is formed by connecting the FTNN and the GNN, and the mapping between the performance index and the design parameters can be established. The inverse design model can automatically output the design parameters in milliseconds once the customized performance index of the target absorber is input.

**III. RESULTS AND DISCUSSION**

**A. DATA COLLECTING**

To train the deep learning model, the data sets should contain massive simulation raw data. An automatic simulation script based on full-wave numerical simulator CST microwave studio has been applied to compute the S11 and S21 parameters of the corresponding absorber to improve the efficiency. Afterwards, the S11 and S21 are used to calculate the absorptivity as:

$$A = 1 - |S_{11}|^2 - |S_{21}|^2$$

(2)

where $A$ represents the absorptivity.

Within the parameter limits, 22500 simulations of MMAs are performed with different geometry parameters which use an appropriate sampling interval sampled from the geometry parameters hyperspace, which is specified in Table 4. The simulation was performed within a spectrum range from 4GHz to 20GHz, and the sampling step in the frequency domain is 0.5GHz. Among all the simulation results, 20000 of them are assigned as the training data sets, the rest are used as the test data sets.

**TABLE 4.** Geometry Hyperspace.

| Parameters | Scale | Interval |
|------------|-------|----------|
| $w_1$      | 3mm-3.5mm | 0.17mm   |
| $w_2$      | 0.5mm-1mm | 0.17mm   |
| $l_1$      | 9mm-10mm | 0.33mm   |
| $l_2$      | 4mm-5mm  | 0.33mm   |
| $l_p$      | 1mm-10mm | 1mm      |
| $r$        | 50Ω/sq-140Ω/sq | 10Ω/sq   |

**B. PREDICTING NEURAL NETWORK MODEL**

The configuration of our computer is Intel(R) Core(TM) i7-6700HQ CPU @ 2.60GHz and GTX1060 6G GPU. The deep learning algorithm is realized with python version 3.7.1 under the Pytorch framework.

In the training stage of the PNN, the Adaptive Moment Estimation(Adam) optimizer is employed which is a widely used optimization algorithm for researchers to train the neural network. The loss function is the least-squares error, also known as Mean Squared Error (MSE). More specifically

$$L_{PNN} = \frac{1}{N} \sum_{i=1}^{N} (A_{\text{prediction}} - A_{\text{simulation}})^2$$

(3)

it measures the distance between the absorptivity ($A_{\text{prediction}}$) generated from the PNN and the simulation results ($A_{\text{simulation}}$) given by simulation in searching space.

The test data set is employed to evaluate the PNN. The absorptivity output by the well-trained PNN has been compared with the absorptivity calculated by full-wave numerical simulation, and several comparisons have been shown in Fig.6. In this picture, the absorptivity output by the PNN and the absorptivity calculated by the simulation...
FIGURE 6. The comparison of simulation results and predicted result of the PNN. Blue curves represent the result of the simulation, which is also the input of our PNN, and red points represent the output of the PNN. The MSE of all the test samples is $2.95 \times 10^{-4}$, and the corresponding error rate is 0.8%. Design parameters $[w_1, l_1, w_2, l_2, t_p, r]$ are given for each design in the insets.

matches well. The MSE of all the test samples is $2.95 \times 10^{-4}$, and the corresponding error rate is 0.8%. These results show excellent consistency between the resulting output of the PNN and numerical simulations results. The error is defined as

$$E_{PNN} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{A_{\text{prediction}} - A_{\text{simulation}}}{A_{\text{simulation}}} \right)^2$$

(4)

Compared to the full-wave numerical simulation, and the PNN is extremely fast that can output the absorber’s absorptivity in milliseconds, which makes the PNN plays a pivotal role in the inverse design model.

C. INVERSE NEURAL NETWORK MODEL

To train the FTNN, the absorbing performance of the absorber is extracted to build the new training and testing data set for the FTNN. In the training process, the FTNN takes the absorbing performance as its input and output the corresponding target absorptivity. The FTNN uses the least-squares error loss function. The test data set have been employed to evaluate the FTNN, and the MSE of all the test samples is $5.75 \times 10^{-3}$. Fig.7 have shown several comparisons of the simulation result of the target absorber and the output spectrum of the FTNN. Although the output spectrum is not as smooth as the simulation result, it still keeps the primary features of the simulation result.

In the training process of the GNN, the FTNN connects with the GNN, and the GNN followed with the well-trained PNN to form a cascaded network, which is demonstrated in Fig.3. The cascaded network can effectively avoid the non-convergence problem [43]. For the GNN, to remain the physical structure of the absorber, a constraint factor of the design parameters is applied to the loss function of the GNN to constrain the choices of design parameters. For example, suppose the sum of $l_1$ and $w_2$ is greater than $p$. In that case, the Jerusalem cross slot will break the edge of the absorber unit cell, and the slot of each unit cell will connect when all unit cells are combined. Thus the loss function of the GNN is defined as

$$L_{GNN} = \frac{1}{N} \sum_{i=1}^{N} (A_{\text{generated}} - A_{\text{target}})^2$$

$$+ \frac{1}{N} \sum_{i=1}^{N} (P_{\text{generated}} - P_{\text{target}})^2$$

(5)
FIGURE 7. The blue curves represent the simulation result of the target absorber, and the red curves are the target spectrum output by the FTNN based on the input customized performance index represented by the black curves. The overall test MSE is \(5.75 \times 10^{-3}\). Design parameters \([w_1, l_1, w_2, l_2, t_p, r]\) are given for each design in the insets.

where \(A_{\text{generated}}\) and \(A_{\text{target}}\) represent the predicted absorptivity and target absorptivity of the designed absorber. \(P_{\text{generated}}\) and \(P_{\text{target}}\) represent the output design parameters and target design parameters. The constraint factor \((P_{\text{generated}} - P_{\text{target}})^2\) will make sure the design parameters located in a reasonable region.

In the training stage, the customized performance index of the target absorber is input to the FTNN, the output of the FTNN is then assigned as the input of the GNN, and the GNN will output the design parameters. The design parameters will be designated as the input of the PNN. The PNN evaluates the absorptivity of the designed absorber, and compares it with the target absorptivity output by the FTNN, the difference between them will be evaluated and propagate back to the GNN as the loss. During the training period, the biases and weights in the hidden layers of the GNN are optimized to minimize this difference, while the biases and weights of hidden neurons in the well-trained PNN and the FTNN remain unchanged. Moreover, the GNN will be evaluated by the test data set every ten times until the GNN is well-trained. As a result, the GNN becomes “smarter” along with training proceeds, the difference between the predicted absorptivity and the target absorptivity will keep reducing until the GNN can generate the qualified absorber design on a one-time calculation.

Fig. 9 shows the accuracy of the model is increases along with the decrease of training loss. The big learning rate is employed at the beginning to fast lower the loss and decrease the training time. After ten epoch, the learning rate is reasigned to a smaller value and keeps train the model to its limits. The test data set is employed to appraise the validity of the proposed model, the MSE of all the test samples is \(2.9 \times 10^{-3}\), and the corresponding error rate is 6.5%.

To demonstrate the capability of this inverse model, full-wave numerical simulations are utilized to verify pattern of the unit cell generated by the GNN. Several representative cases are shown in Fig. 8.

| TABLE 5. The Training Hyperparameters of Each Neural Network Model. |
|----------------|----------------|-----------------|-----------------|
| DNN   | Learning rate | Batch size | Number of epochs | Optimizer |
| PNN   | \(1x10^{-5}\)  | 100        | 1250             | Adam          |
| FTNN  | \(1x10^{-5}\)  | 100        | 1250             | Adam          |
| GNN   | \(1x10^{-5}\)  | 100        | 1250             | Adam          |

In Table 5, the training hyperparameters of each neural network model have been listed. And the errors are
The red points represent the spectrum of the target absorber, and the blue curves represent the predicted spectrum based on the design parameters given by the GNN. The green curves represent the simulation results based on the design parameters given by the GNN. The black curves represent the customized performance index of the target absorber. And the MSE of all the test samples is $2.9 \times 10^{-3}$, and the corresponding error rate is 6.5%. Design parameters $[w_1, l_1, w_2, l_2, t_p, r]$ are given for each design in the insets.

According to the different outputs of the neural network model, the $E_{\text{Parameters}}$ is used to evaluate the GNN, and the $E_{\text{Spectrum}}$ is used to evaluate the PNN and the FTNN.

**IV. DISCUSSION**

For further analysis, we have verified some cases that are not in our previous data set. Those cases can be classified into two types: the first type is obtained by only change the absorption band of the existing performance indexes data; The second type is obtained by randomly change the slope of the existing performance indexes data. The result indicates that the broader absorbing spectrum may influence the output accuracy of the FTNN and the GNN, but the random slope may cause nonconformity output, especially when the slope is too steep or reversed. Some typical cases have been shown in fig.10.

We also classified the test sample by different value of the resistive parameter, all the test sample is divided into ten groups from $r = 50$ to $r = 140(\Omega/$sq) with an interval of 10$\Omega$/sq and its MSE and error rate is listed in Table 5.

Table 6 list the MSE, and the corresponding error rate of different resistance, the MSE and error rate of each group are

\[
E_{\text{Parameters}} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{P_{\text{generated}} - P_{\text{target}}}{P_{\text{target}}} \right) 
\]

\[
E_{\text{Spectrum}} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{A_{\text{prediction}} - A_{\text{target}}}{A_{\text{target}}} \right) 
\]
FIGURE 10. This figure has shown some represented cases, fig(a) and fig(c) is the result of the performance index with reversed slope and a much steeper slope, and fig(b), (d) are results when the performance index with broader absorbing spectrum.

TABLE 6. MSE and Error Rate of Each Group of Different Resistance.

| Resistance(Ω/sq) | MSE   | Error rate(%) |
|------------------|-------|---------------|
| r=50             | 0.0034| 7.2           |
| r=66             | 0.0031| 6.9           |
| r=70             | 0.0025| 6.3           |
| r=80             | 0.0032| 6.8           |
| r=90             | 0.0034| 6.4           |
| r=100            | 0.0023| 5.9           |
| r=110            | 0.0025| 6.1           |
| r=120            | 0.0024| 6.0           |
| r=130            | 0.0028| 6.3           |
| r=140            | 0.0032| 7.0           |

close to the MSE and error rate of the whole test sample. This result indicates that this neural network model effectively generalizes the relationship between the resistance of the resistive film and the performance of the absorber. Furthermore, it also exhibits a promising prospect for introducing the physical characteristics of the constitution material to the deep-learning-based method, such as permittivity, permeability, refractive index.

V. CONCLUSION

In this article, we proposed a target-driven method to design the MMA according to the customized requirement. The deep learning methodology is introduced into this method. An inverse design model is constructed and trained to uncover the congruent relationship between MMAs design parameters and its absorptivity spectrum. The design parameters of the target MMA can be generated automatically in milliseconds once the customized performance index of the target MMA is input into the inverse design model.

Compared to the conventional MMAs design method, the target-driven deep-learning-based method avoids vast full-wave numerical simulation and realizes the on-demands design of MMAs in few seconds. Unlike previously proposed deep-learning-based methods, which directly map the target spectrum to the design parameters, the target-driven method uses the sampled S-parameter spectrum as the intermediary to connect the customized performance index and the design parameters, which makes our method more in line with the practical design needs. Besides, the compatibility of this method is strong. In our work, the surface resistance of the composition materials is introduced into the design parameters, and a good result has been achieved, which indicates that other physical characteristics are valid. This method is also suitable for other MM devices by changing the training datasets. It is worth noting, by substitute convolution neural network for DNN, the proposed method can be employed to design more complicated devices where the unit cell is too
complicated to parameterized. We envision that this deep-learning-based method can be expanded to the design of other complex MM devices, such as antennas, integrated optical circuit devices, hologram and microwave components.

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