Artificial Neural Network based Design of RF MEMS Capacitive Shunt Switches

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Abstract **─** Artificial neural networks (ANNs) have appeared as a very efficient alternative to time consuming full-wave simulations of electrical characteristics of RF MEMS. In this paper, a new ANN based method to be used in the design of RF MEMS devices is proposed. ANNs are trained to model dependence of the scattering parameters and the resonant frequency of an RF MEMS switch on the switch geometrical parameters, as well as to perform the opposite procedure, i.e., to determine values of the geometrical parameters to achieve the desired electrical resonant frequency. The developed models can be used for fast simulation and optimization of the switch characteristics replacing time consuming procedures in full-wave simulators, which leads to a significant reduction of time needed for the device design.

Index Terms **─** Artificial neural networks, computer aided design, RF MEMS.

I. INTRODUCTION

RF MEMS switches are of growing interest for use in various communication and measurement systems, as they possess some properties superior to their mechanical or electronic counterparts [1-4]. They are lightweight, small, extremely linear, can be integrated and allow easy re-configurability or tunability of a system. A simulation of electrical parameters of RF MEMS components can be performed using standard commercial electromagnetic simulators. However, due to the aspect ratio of the vertical and lateral dimensions and the 3D topology, a full-wave simulation becomes time consuming. If the switch is integrated in a larger system, the desired overall system performance requires a certain behavior of the switch, e.g., in case of the capacitive shunt switch it is the position of the resonance in a given frequency range. To achieve the required performance, time consuming optimizations should be performed, i.e., calculations of the switch with varying parameters have to be repeated. This paper demonstrates how the synthesis of the required switch performance can be accelerated by developing an ANN based model of the switch.

ANNs have been already applied to model some electrical or mechanical characteristics of different RF MEMS devices [5-11]. They have been applied mostly to the models of RF MEMS resonators [5, 9], and to the RF MEMS switches [6-8, 10, 11]. As far as the RF MEMS switch electrical characteristics are concerned, the ANNs have been applied for developing ANN models of the switch scattering parameters based on the frequency and switch geometrical parameters [6, 7], or for modeling the resonant frequency dependence on the switch geometrical parameters [11]. Also, it has been shown how some of the developed ANN models can be used in the design of circuits containing the modeled devices [10].

This contribution presents a neural modeling approach of a capacitive coplanar shunt switch. For the considered device, neural models for dependence of the switch electrical characteristics, i.e., the scattering parameters and resonant frequency, on the switch dimensions are developed. Also, a new approach for the inverse process, i.e., determination of the switch dimensions to achieve the desired switch performance, avoiding full-wave optimization procedures is proposed.

The paper is organized as follows: after introduction, in Section II the considered device is described. In Section III, a brief background on ANNs is given. In the following section the ANN based feed-forward models for determination of switch electrical characteristics for the given switch geometrical parameters are described, as

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some of them are further used for building the inverse models. The proposed inverse models are described in Section V. Further, details of the proposed modeling technique and the obtained numerical results are presented and discussed in Section VI. Finally, Section VII contains concluding remarks.

II. DEVICE DESCRIPTION

The considered device is an RF MEMS capacitive coplanar shunt switch, depicted in Fig. 1, fabricated at Fondazione Bruno Kessler (FBK) in Trento, Italy in an 8 layer Silicon micromachining process [12]. The signal line below the bridge is realized as a thin aluminum layer. Adjacent to the signal line the DC actuation pads made of polysilicon are placed. The bridge is a thin membrane connecting both sides of the ground. The inductance of the bridge and the fixed capacitance between signal line and bridge form a resonant circuit to ground. The resonant frequency can be changed by varying the length of the fingered part, L_f, close to the anchors and the solid part, L_s. At the series resonance the circuit acts as a short circuit to ground, in a certain frequency band around the resonant frequency the transmission of the signal is suppressed. The bridge can be closed by applying the actuation voltage of around 45 V.

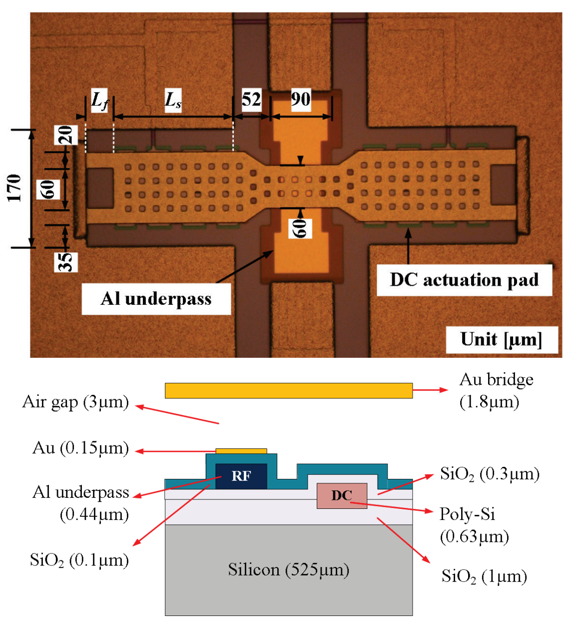


Fig. 1. Top-view of the realized RF MEMS switch and schematic of the cross-section with 8 layers in FBK technology [12].

III. ARTIFICIAL NEURAL NETWORKS

In this work standard multilayer perceptron (MLP) neural networks are exploited. An MLP ANN consists of basic processing elements (neurons) grouped into layers: an input layer (IL), an output layer (OL), as well as several hidden layers (HL) [13]. Each neuron is connected to all neurons from the adjacent layers, whereas there are no connections among neurons belonging to the same layer. A neuron is characterized by a transfer function and each connection is weighted. In this work the following neuron transfer functions are used: linear transfer function for the input and output neurons and sigmoid transfer function for the hidden neurons. Information flows forward from the input layer to the output layer. An ANN learns relationship among sets of input-output data (training sets) by adjusting network connection weights and thresholds of activation functions. There is a number of algorithms for training of ANNs. The most frequently used are backpropagation algorithm and its modifications, as the Levenberg Marquardt algorithm [13], used in the present work. Once trained, the network provides fast response for various input vectors without changes in its structure and without additional optimizations. The most important feature of ANNs is their generalization ability, i.e., ability to generate a correct response even for the input parameter values not included in the training set. The generalization ability has qualified ANNs to be used as an efficient tool for modeling in the field of RF and microwaves [5-9, 13-24]. As examples, ANNs could be used as an alternative to time-consuming electromagnetic simulations [7, 13, 20, 23] or an alternative to the conventional modeling of microwave devices [14, 17, 22, 24].

IV. FEED-FORWARD RF MEMS SWITCH MODELING

As mentioned in the introductory section, ANNs can be applied to develop models of the electrical characteristics of RF MEMS switches. It should be noted that in the work of the other authors, the simple rectangular shape membrane has been studied. This is the first time that a membrane with complex structure and shape is considered to be modeled by ANNs.

Two types of the models are developed here. The first type of the models is based on ANNs trained to predict the switch scattering parameters dependence on the switch geometrical parameters and frequency, whereas in the second type of the models ANNs are exploited to model dependence of the switch electrical resonant frequency on the switch geometrical parameters. Figures 2 and 3 show the mentioned ANN models developed for the considered capacitive shunt switch.

The considered geometrical parameters are the lengths of the fingered and solid parts, L_f and L_s, as illustrated in Fig. 1.

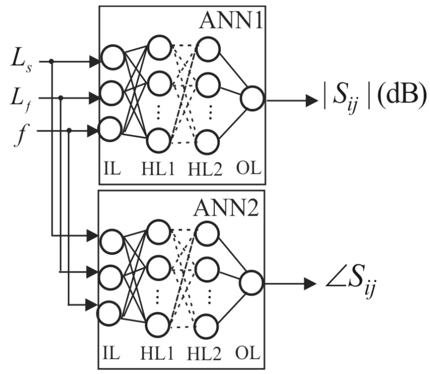


Fig. 2. ANN model of RF MEMS switch S-parameters.

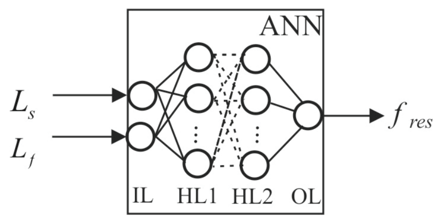


Fig. 3. ANN model of RF MEMS switch resonant frequency.

As far as an RF MEMS switch is a symmetric and reciprocal device, i.e., $S_{22}=S_{11}$ and $S_{12}=S_{21}$, it is enough to develop only models for S_{11} and S_{21}. For each of the modeled parameters, two ANNs are trained, one to model the magnitude ($|S_{ij}|$) and the other to model the phase $(\angle S_{ij})$. As the training data, the S-parameters calculated in numerical full-wave simulations in an electromagnetic simulator are used. Each ANN has three input neurons corresponding to the two lateral dimensions of the switch and the frequency, and one output neuron corresponding to the modeled parameter. The model is validated by comparing the ANN response and the full-wave simulation results for the combination of dimensions not seen by the ANN during the training. Once the ANNs are trained, the S-parameters of the switch can be easily calculated in a very short time by finding the ANN response. In order to use the developed ANN model in a circuit simulator for the switch S-parameter simulation and optimization, the expressions describing the ANNs are implemented in the simulator. Namely, the switch is represented by a two-port expression defined device. The expressions describing the ANNs are put into variable and equation blocks (VAR) having the switch lateral dimensions and frequency as input parameters and switch S-parameters as outputs. The S-parameters calculated in the VAR blocks are assigned to the two-port device S-parameters. Therefore, the two-port device and the corresponding VAR blocks represent the ANN model of switch with included dependence on the geometrical parameters. The overall procedure of model development and implementation is shown in Fig. 4. Once the ANN model of the switch scattering parameters is implemented in a circuit simulator, further simulations and optimizations are performed in a standard way, but in significantly shorter time, as will be illustrated later.

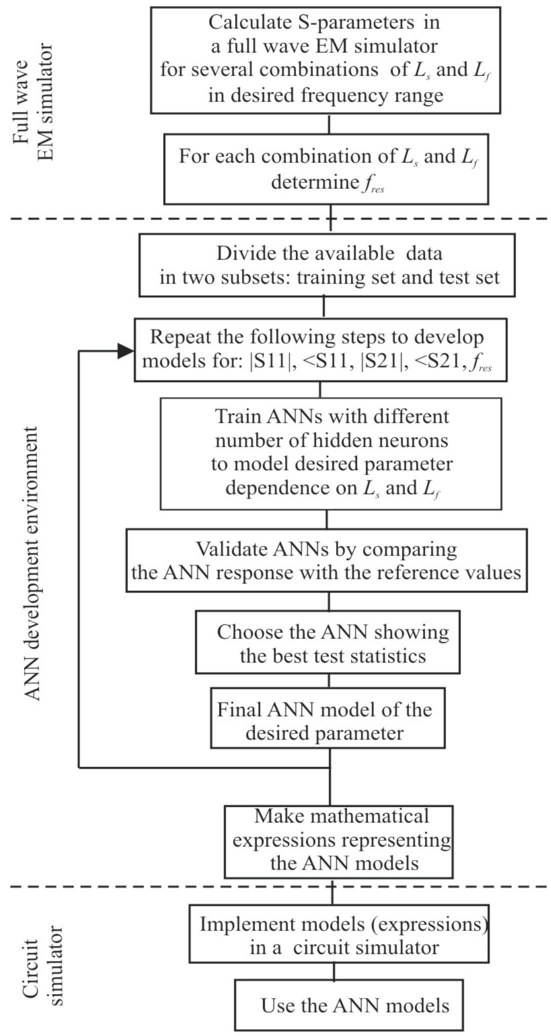


Fig. 4. ANN model development and implementation.

The neural model for the switch resonant frequency consists of an ANN trained to model the switch resonant frequency dependence on the two mentioned lateral dimensions. Therefore, the ANN has two neurons in the input layer and one neuron in the output layer. As in the previous case, the data used for training and validation of the ANN are obtained by the full-wave numerical simulations.

The developed model can be further used to determine the resonant frequency for given values of the lateral dimensions in a very short time or to optimize the dimensions to achieve the desired resonant frequency.

It is worth to mention that the ANN models are valid for the values of the lateral dimensions falling within their ranges used in the training set.

V. INVERSE RF MEMS SWITCH MODELING

With the aim to avoid optimization procedures in full-wave electromagnetic or circuit simulators, the inverse RF MEMS switch modeling approach based on ANNs is also proposed here. This gives the possibility to directly determine the necessary geometrical dimensions for a desired resonant frequency. The idea is to train ANNs with the aim to directly predict one of the switch geometrical parameters in order to satisfy working conditions around the resonance when the other parameter is fixed, as shown in Fig. 5. Namely, ANNs are trained to learn the relationship between the chosen lateral switch dimension and resonant frequency and the other switch dimension. Therefore, the ANNs have two input neurons and one output neuron. The training and test data are obtained by standard full-wave simulations. By using the trained ANNs, the considered geometrical parameter values could be determined by a simple calculation of the ANN response. In that way design of the RF MEMS switch becomes more efficient.

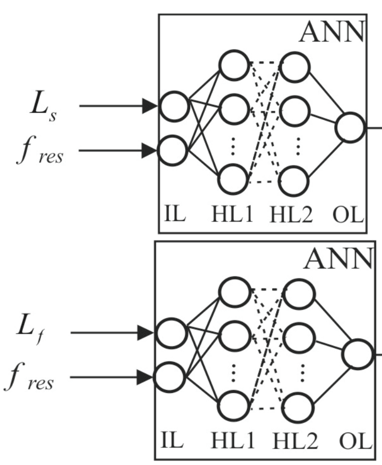


Fig. 5. ANN based determination of RF MEMS switch geometrical parameters.

VI. NUMERICAL RESULTS

The data used for the ANN model development and validation was obtained by full-wave simulations within ADS software package (ADS momentum) [25] for the frequencies up to 40 GHz. As the number of hidden neurons could not be determined prior to the training process, for each ANN, ANNs with different number of hidden neurons were trained and then the ANN showing the best modeling results was chosen as the final one.

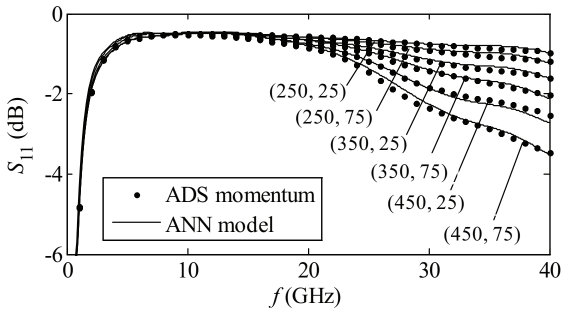
A. Feed-forward RF MEMS switch models

The S-parameters used for the model development were simulated in ADS momentum for 23 combinations of geometrical parameters L_f and L_s. The data referring to 17 combinations was used for training and the data referring to the rest of 6 combinations was used for validation of the model generalization. As mentioned above, for each of the modeled parameters ANNs with different number of hidden neurons were trained and compared. The ANN accuracy was compared by assessing the errors obtained for the test values not used for training. It was found that among the trained ANNs the best test statistics gave the following two-hidden-layer ANNs: for the magnitude of S_{11}: the ANN having 8 neurons in the first layer and 6 neurons in the second hidden layer, and for the magnitude of S_{21}: the ANN with 8 neurons in both hidden layers. For models of the phases in both cases the best results were obtained by the two hidden-layer ANNs containing 10 neurons in each hidden layer. As illustration, Figs. 6 and 7 show comparison of the ANN simulated scattering parameters (lines) and the corresponding reference values obtained by the full-wave simulations in ADS (symbols). It can be concluded that the ANN responses match very well with the simulated values. As the ANN model directly relates the switch lateral dimensions to the scattering parameters over frequency, the S-parameters of a varied geometry can be calculated within seconds.

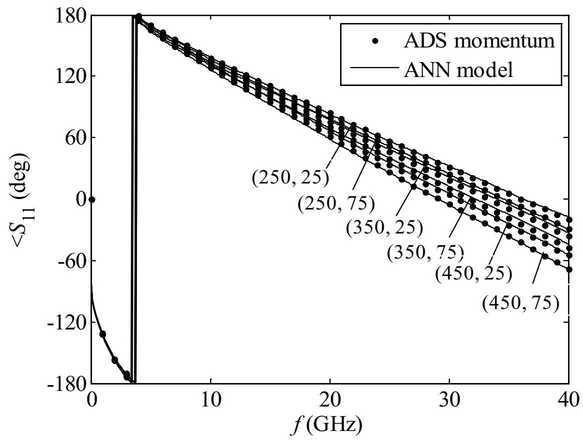
Optimization of the dimensions for the given requirements in the desired frequency band lasts less than a second when performed by using the neural model implemented in the ADS circuit simulator in a way described in the previous section, which is significantly faster than the optimization in a full wave simulator, which lasts around 2 hours.

To confirm further the achieved good modeling accuracy, magnitude of the transmission coefficient of the fabricated device (L_s = 174 μm and L_f = 40 μm) optimized for a resonant frequency of 15 GHz is depicted in Fig. 8. The plot shows the measured data (dashed line) in comparison with the results of the ANN model (line) and the full-wave simulations (symbols).

To develop a model for the resonant frequency, first the resonant frequency for all the combinations of dimensions of the geometrical parameters L_s and L_f considered in the previous case was determined. The resonant frequency was found as the frequency corresponding to the minimum value of magnitude of S_{21} simulated in a full-wave simulator. The training and test set correspond to the same geometrical parameter combinations as in the previous case. Among the trained ANNs with different number of hidden neurons, the best results were obtained by the ANN having only one hidden layer containing five neurons. Table 1 shows the resonant frequency determined by the ANN model for several combinations of the geometrical parameters not used for the training. It can be seen that the resonant frequency values simulated by the ANN are very close to the target values, as confirmed by the relative percentage error less than 1%.

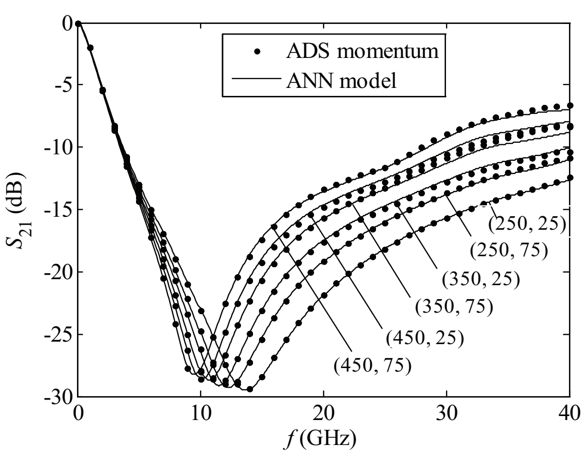


(a)

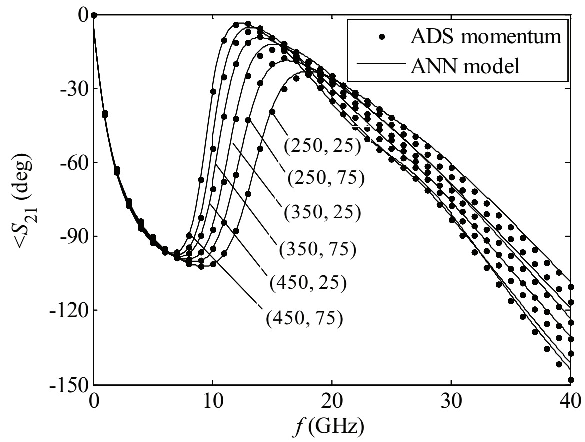


(b)

Fig. 6. Parameter S_{11} for six (L_s [μm], L_f [μm]) combinations not used for the model development: (a) magnitude and (b) phase.



(a)



(b)

Fig. 7. Parameter S_{21} for six (L_s [μm], L_f [μm]) combinations not used for the model development: (a) magnitude and (b) phase.

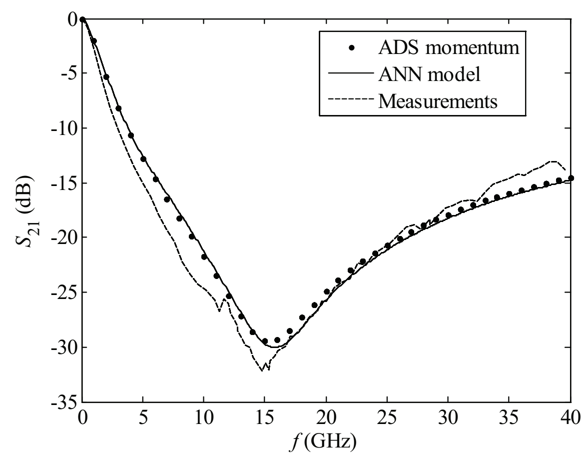


Fig. 8. Isolation of the fabricated RF MEMS switch (L_s = 174 μm and L_f = 40 μm).

Table 1: RF MEMS switch resonant frequency

L_s (μm)	L_f (μm)	$f_{res\text{-}Target}$ (GHz)	$f_{res\text{-}ANN}$ (GHz)	Rel. Error (%)
250	25	13.7	13.689	0.08
250	75	12.4	12.403	0.02
350	25	11.6	11.550	0.43
350	75	10.7	10.638	0.58
450	25	10.2	10.127	0.71
450	75	9.5	9.499	0.01

B. Inverse RF MEMS switch models

The inverse models described in Section V were developed using the full-wave simulated data referring to the same 23 combinations of the switch lateral dimensions as used for the development of the feed-forward models. It appeared that the accuracy of the modeling was not satisfactory, as the errors during the model validation achieved even several tens percent. This indicates that a larger training set should be used to build reliable inverse ANN models. Acquiring more training data needed for the inverse ANN models assumes new full-wave simulations, as the resonant frequency for each new combination of input geometrical parameters is determined by a full-wave simulation. To make a larger training set, but without significant increase of the model development time, the feed-forward ANN model for the resonant frequency described above was used. As this ANN model gives a response almost in a moment, building a larger data set does not increase significantly the duration of the model development procedure. For building a new larger training dataset, a non-uniform distribution of combinations of the dimensions was used. The number of data in the areas of the input parameter space where the ANN models showed higher error values was increased until the satisfactory accuracy of the inverse ANNs model was reached. The final training dataset referred to 814 input-output pairs. During the ANN model development procedure, the ANNs with different number of hidden neurons were trained and validated on the set of data not used for the training purpose. Among the trained ANNs, the ANNs with two hidden layers with 15 neurons in each hidden layer were chosen for the both lateral dimensions determination.

To illustrate the accuracy of the inverse RF MEMS ANN models, in Tables 2 and 3 there are results of the model testing for the input combinations not used for the ANN training. It should be noted that the resonant frequency values given in the tables are calculated in the full-wave simulator for the combination of input dimension and target output dimension.

It can be seen that the absolute difference of the predicted and expected values is less than 3 µm (which is already close to fabrication tolerances) in the case of modeling the length of fingered part, and less than 3.5 µm, in the case of modeling the length of solid part. The relative errors are in most cases less than 3%.

Table 2: RF MEMS switch inverse modeling: L_f

L_s (µm)	f_{res} (GHz)	L_f (Target) (µm)	L_f (ANN) (µm)	Relative Error (%)
75	22.78	25	24.9	0.4
75	19.17	65	65.4	0.6
75	17.92	85	85.3	0.3
100	17.5	75	73.6	1.9
200	13.13	85	86.8	2.1
350	11.67	25	23.4	6.4
350	10.83	65	62.2	4.3
400	10	85	87.4	2.9

Table 3: RF MEMS switch inverse modeling: Ls

L_f (µm)	f_{res} (GHz)	L_s (target) (µm)	L_s (ANN) (µm)	Relative Error (%)
25	22.78	75	74.9	0.1
65	19.17	75	75.5	0.7
85	17.92	75	75.3	0.4
75	17.5	100	97.9	2.1
85	13.13	200	202.7	1.4
25	11.67	350	347.8	0.6
65	10.83	350	348.0	0.6
85	10	400	403.4	0.9

VII. CONCLUSION

At the example of a capacitive coplanar shunt switch in RF MEMS technology, efficient ways for determination of the switch geometrical parameters based on the ANNs were presented. Usage of the proposed ANN models can be an efficient alternative to the standard optimization of the switch dimensions in the full-wave simulators. First, feed-forward models based on ANNs were trained to determine the switch electrical characteristics for the given values of the considered geometrical parameters. Then, inverse ANN models for determination of the switch geometrical parameters for the given switch resonant frequency were developed.

Once developed the proposed ANN models can be used for obtaining further results within seconds, which is much faster than full-wave EM simulations and optimizations lasting up to 2 hours. Having in mind that training a number of ANNs with different number of hidden neurons and long numerical simulations performed to obtain the training data take time comparable to the time needed for the optimization of the single switch, the efficiency of the proposed method is not obvious for a single switch simulation and optimization. However, the speed of the ANN models comes out as an advantage for a settled technology, when a number of switches with slight variations have to be adjusted to fulfill requirements for different applications without using heavy and time-consuming full-wave simulators, thus speeding up significantly the fabrication cycle.

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