ANN Based Inverse Electro-Mechanical Modeling of RF MEMS Capacitive Switches

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Abstract – **In this paper an artificial neural networks (ANN) based approach for the development of an inverse electro-mechanical model of capacitive RF MEMS switch is presented. The ANN model is aimed to predict length of the fingered part of the switch for fixed length of the solid part of the bridge, resonant frequency and actuation voltage. In this way, for the given length of the bridge solid part, the bridge fingered part length needed to achieve the requested resonant frequency with the chosen actuation voltage can be instantaneously found. The obtained results confirm the efficiency and accuracy of the proposed approach.**

Keywords –**Artificial neural networks, RF MEMS, capacitive switch, inverse modeling, actuation voltage, resonant frequency.**

I. Introduction

RF MEMS switches are often used in modern communication and measurement systems since they have numerous advantages over their mechanical or electronic counterparts. RF MEMS switches are very small, extremely linear, can be integrated and allow easy re-configurability or tunability of a system [1].

Therefore, the design of the circuits containing RF MEMS switches requires the presence of reliable and accurate models. The modeling of RF MEMS switches is conventionally performed using standard commercial electromagnetic simulators [2]-[3]. However, those simulations are time consuming and require considerable computing resources because RF MEMS switches normally consist of several complex thin layers and via connections of micro-scale.

Artificial neural networks (ANNs) [4] have appeared as an efficient alternative to build the models able to determine the switch characteristics in a very short time, reducing in that way the time needed for the simulation of circuits containing the considered switches [5]-[10].

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In the previous papers [9-10], ANN based models of RF MEMS capacitive switches are developed. ANNs are used to predict the switch S-parameters for the given values of frequency and geometrical lateral dimensions of the switch bridge [9]. Having in mind that very often it is not necessary to determine frequency dependence of the scattering parameters, but just to have information about the resonant frequency change with the change of switch geometry parameter values, a new ANN model trained to predict the resonant frequency for the given lateral dimensions of the bridge is proposed [9]. Similar ANN model that can be applied to model the chosen mechanical parameter of the switch - actuation voltage on the considered switch geometrical parameters as inputs is also developed, [10]. ANN models that model the electrical resonance frequency or actuation voltage for the given lateral dimensions of the switch are called direct ANN models. It is shown that optimization process is significantly reduced by the usage of those models instead of the standard EM/mechanical simulators, but still there is a need for the optimizations. In order to avoid optimizations completely, a new approach based on ANN for the switch inverse modeling is proposed, [10]. The procedure is demonstrated at the example of the capacitive switch, where the length of the fingered part is determined for a given length of the solid part of the bridge and electrical resonance frequency / actuation voltage.

Since electrical and mechanical characteristics of the switch are not mutually independent, the optimization of the dimensions should be performed simultaneously in the EM and mechanical simulator, which can be very complex and time consuming. Therefore, in this paper we propose a further extension of the procedure suggested in [10]. Namely, the idea is to extend the inverse ANN models shown in [10] to combine mechanical and electrical parameters of the switch. The new inverse electro-mechanical ANN model has resonant frequency, actuation voltage and length of the solid part of the bridge as the inputs and the length of the fingered part as the output, as it will be described later.

The paper is organized as follows: after Introduction, in Section II a brief background on the ANNs is given. In Section III the capacitive RF MEMS switch modeled in this work is described. An inverse electro-mechanical ANN model is proposed in Section IV. Further, details of the proposed modeling technique and the obtained numerical results are presented and discussed in Section V. Finally, Section VI contains concluding remarks.

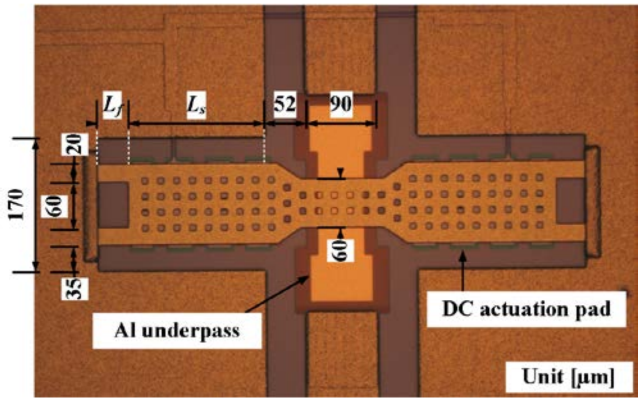
II. ARTIFICIAL NEURAL NETWORKS

In this work, multilayered ANNs are used in this work [4]. A multi-layered ANN consists of layers of neurons: an input layer, an output layer, as well as one or more hidden layers. The number of neurons in the input layer equals to the number of independent input parameters, whereas the number of the output neurons equals to the number of parameters modeled by the ANN. An ANN is trained to learn dependencies between two data sets by optimization of thresholds of the neuron activation functions and the neuron connection weights. Once trained ANNs give instantaneous response for different combinations of the input parameter values, no matter if they have been used for the model development or not. The ANN generalization, i.e., their ability to give the correct response for the input values not used for their training, qualified them as an efficient modeling tool in the field of RF and microwaves [1], [11-14].

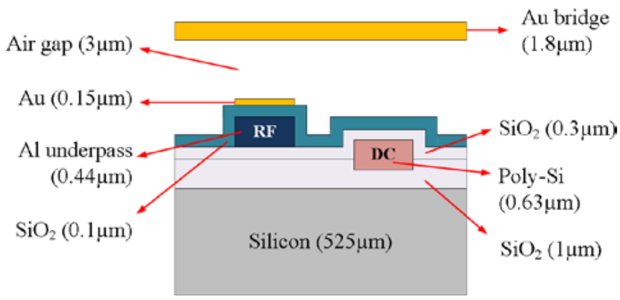
III. DEVICE DESCRIPTION

The considered device is an RF MEMS capacitive coplanar shunt switch, depicted in Fig. 1, fabricated at FBK in Trento in an 8 layer Silicon micromachining process [11]. The signal line below the bridge is realized as a thin aluminum layer. Adjacent to the signal line the DC actuation pads made by 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 an actuation voltage of around 45V.

The actuation voltage is determined as the instant voltage applied to the DC pads when the bridge comes down and touches a coplanar waveguide centerline, which is a pull-in voltage (V_{PI}). This is strongly related to the switch features and mechanical/material properties, such as a DC pad size and location, a bridge spring constant and residual stress, bridge shapes or supports, etc. The finger parts (correspond to L_f) in Fig. 1 are to control V_{PI}. If finger parts are long compared to the other parts, the bridge becomes flexible and the switch is easily actuated by a low V_{PI}. But this increases the risk of a self-actuation or an RF hold-down when the switch delivers a high RF power. And opposite, with the short finger parts, the switch needs a high V_{PI} to be actuated. Therefore, the bridge part lengths (L_f, L_s) should be carefully determined considering a delivering RF power and a feasible DC voltage supply [1].



a)



b)

Fig. 1. a) Top-view of the realized switch; b) schematic of the cross-section with 8 layers in FBK technology [11]

IV. PROPOSED INVERSE ELECTRO-MECHANICAL ANN MODEL

An ANN model for inverse electro-mechanical modeling of RF MEMS capacitive switch is proposed. As it is mentioned in the introductory section, the idea is to train an ANN to calculate the length of the bridge fingered part, L_f, for the fixed value of the solid part, L_s, in order to obtain a desired electrical resonant frequency, f_{res}, having a chosen actuation voltage, V_{PI}. Therefore, the ANN has three inputs corresponding to L_s, f_{res} and V_{PI}, and one output corresponding to L_f, as shown in Fig. 2.

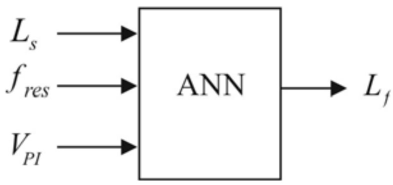


Fig. 2. Proposed inverse electro-mechanical ANN model.

The training data necessary for model development is acquired by simulations. Namely, for certain number of combinations of L_f and L_s the corresponding resonant frequency values and actuation voltage values should be calculated in appropriate EM / mechanical simulators. Alternatively, these values can be determined by using the neural models relating the bridge lateral dimensions with the resonant frequency and the actuation voltage, as shown in [10] in the case of inverse electrical/mechanical models. The advantage of using such direct neural models for generating the training data, over using the standard EM/mechanical simulators, is that an arbitrary sized training set can be generated in a very short time.

Once trained, the developed ANN model can be used for determination of L_f instantaneously for given L_s, f_{res} and V_{PI} without any further optimization.

IV Numerical Results

The ANN models of the considered switch were developed for the following ranges of the switch geometrical parameters: L_s from 100 µm to 500 µm, and L_f from 0 µm to 100 µm.

The training data was obtained by using the direct neural models of the switch resonant frequency and actuation voltages, as described in [10]. The training set referred to 4131 combinations of L_f and L_s values. For the ANN training, Levenberg-Marquardt algorithm, a modification of the most frequently used optimization backpropagation algorithm, was used [4]. Since the number of hidden neurons of an ANN cannot be a priori set, ANNs with different number of hidden neurons were trained and tested. After their assessment the network with the best modeling results is chosen as the final neural model. The best results were achieved by the ANN having two hidden layers containing 10 and 20 neurons, respectively.

The test set referred to 40 combinations of L_f and L_s values, and the corresponding values of the resonant frequency (calculated in ADS momentum [15]) and actuation voltage (calculated in COMSOL Multiphysics [16]).

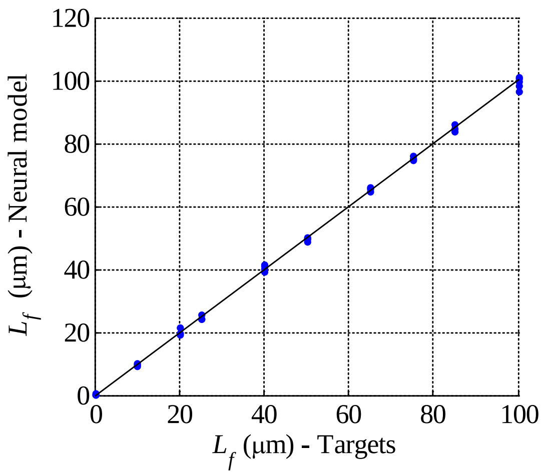


Fig. 3. The length of the fingered part of the switch Scattering plot: ANN model vs. reference data

The proposed neural model provides good modelling accuracy, as can be confirmed by the scattering plot given in Fig. 3 where the values of the L_f obtained by chosen ANN are shown versus the corresponding target values for L_f. There is a very small scattering from the ideal diagonal line $y=x$ indicating a good modelling accuracy.

With the aim of further accuracy investigation of the proposed neural model, for f_{res}=12 GHz and V_{PI} = 75 V. it was examined how the L_f values obtained by the proposed model affect the values of the corresponding resonant frequency and actuation voltage. Namely, the L_f values obtained by the proposed inverse electro-mechanical ANN model

$$L_{f\_inv} = f_{ANN\_inv}\left(L_{s,}\ V_{PI,}\ f_{res}\right) \tag{1}$$

are used as inputs in direct ANN models to obtain resonant frequency and actuation voltage, respectively:

$$f_{res\_dir} = f_{ANN\_dirE}\left(L_{f\_inv,}\ L_s\right), \tag{2}$$

$$V_{PI\_dir} = f_{ANN\_dirM}\left(L_{f\_inv,}\ L_s\right). \tag{3}$$

These values are then compared with the initial f_{res} and V_{PI} values used as the inputs of the inverse model, and the corresponding absolute (*AE*) and relative errors (*RE*) were calculated and shown in shown in Table I and Table II. The following labels are used:

$$AE_{f_{res}} = \left|f_{res\_dir} - f_{res}\right|, \tag{4}$$

$$AE_{V_{PI}} = \left|V_{PI\_dir} - V_{PI}\right|, \tag{5}$$

$$RE_{f_{res}} = AE_{f_{res}} / f_{res}, \tag{6}$$

$$RE_{V_{PI}} = AE_{V_{PI}} / V_{PI}, \tag{6}$$

It can be seen that the errors are smaller than 2%, confirming very good modeling accuracy.

TABLE I
RF MEMS switch modeling results: f_{res}

L_s [µm]	f_{res} [GHz]	V_{PI} [V]	L_{f_inv} [µm]	f_{res_dir} [GHz]	$AE_{f_{res}}$ [GHz]	$RE_{f_{res}}$ [%]
280	12	25	71.35	11.886	0.114	0.95
290	12	25	61.703	11.859	0.141	1.20
300	12	25	52.228	11.827	0.173	1.40
310	12	25	43.426	11.789	0.211	1.80
320	12	25	35.355	11.755	0.245	2.00
330	12	25	26.917	11.884	0.116	0.97
340	12	25	16.59	12.009	0.009	0.07

TABLE II

RF MEMS SWITCH MODELING RESULTS: V_{PI}

L_s [μm]	f_{res} [GHz]	V_{PI} [V]	L_{f_inv} [μm]	V_{PI_dir} [V]	$AE_{V_{PI}}$ [V]	$RE_{V_{PI}}$ [%]
280	12	25	71.350	25.169	0.169	0.68
290	12	25	61.703	25.143	0.143	0.57
300	12	25	52.228	25.120	0.120	0.48
310	12	25	43.426	25.082	0.082	0.33
320	12	25	35.355	25.056	0.056	0.22
330	12	25	26.917	25.129	0.129	0.52
340	12	25	16.590	25.380	0.380	1.50

V. CONCLUSION

In this paper an ANN based procedure for the development of inverse electro-mechanical model of capacitive RF MEMS switch has been presented. The ANN model is aimed to predict length of the fingered part of the switch for fixed length of the solid part of the bridge, resonant frequency and actuation voltage. Unlike the standard switch optimization procedures, where it is necessary to perform complex time-consuming optimizations in the EM and mechanical simulators to optimize the switch dimensions in order to achieve the requested resonant frequency and actuation voltage, in the proposed approach the ANNs are used to determine the desired dimension without optimizations. Optimizations in EM and mechanical simulations, are replaced with the optimizations needed for training the ANNs, but once the ANNs have been trained the length of the fingered part of the bridge could be obtained by simple calculation of the ANN response. This model is especially useful in the cases when it is necessary to perform many optimizations of the same structure.

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