The Lateral Dimension of the Artificial Neural Networks Switches with the Neural Approach

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ABSTRACT: *Inverse modelling of RF MEMS switches is addressed with the neural approach in this work. We use element circuits to develop this approach. The lateral dimension of the switches' artificial neural networks will be beneficial for measuring the lumped elements. The element circuits will help the bridge's lateral dimension. We compared the switch dimension received by the inverse model used to confirm the proposed model. The values recorded from the proposed approach are studied.*

Keywords: Artificial Neural Networks, Inverse Modeling, RF MEMS Switches

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1. Introduction

RF switches are among the most important components of RF transceivers. In the recent years RF MEMS switches have been becoming widely used owing to the advantageous properties that they have comparing to their mechanical and semiconductor counterparts. They are very small, extremely linear, can be integrated and allow easy re-configurability or tunability of a system [1].

An RF MEMS switch has an actuation section and an electrical element which can be categorized according to [1] -[4] :

- Actuation scheme: To electrostatic, magnetostatic, piezoelectric and thermal;

- Geometrical configuration: To vertical configuration and horizontal configuration;

- Electrical configuration: To ohmic contact / series circuit and capacitive / shunt circuit. The series switch has a switch series in the signal path. The shunt switch has a switch parallel to the signal path [4].

In this work a capacitive shunt RF MEMS switch is considered [5].

Design of RF MEMS switches requires reliable and accurate models. Modeling is performed simultaneously in standard full-wave electromagnetic simulators and in mechanical simulators. The simulations are quite time consuming, which is especially emphasized when optimization of the switch dimensions is to be performed to meet the desired electrical or mechanical properties.

In the case of series shunt switches, important dimensions to be optimized are lateral dimensions of the switch bridge, as it will be described in details in Section H. RF MEMS switch modeling based on the artificial neural networks (ANNs) [6] has been proposed as a suitable alternative to the standard modeling approach [7]-[17]. Having in mind that the ANNs have a very short response time, by exploiting the ANN models the process of simulation and optimization of the RF MEMS switches can be speed up. Moreover, as a further improvement of the design and modelling efficiency, inverse models of RF MEMS switches based on ANNs have been developed [12]-[17]. The inverse models are trained to calculate the switch bridge dimensions for given switch resonant frequency and/or switch actuation voltage.

In this paper the inverse modeling approach is extended to the lumped element equivalent circuit model. Namely, inverse modeling assumes determination of the switch bridge dimensions for given values of the equivalent circuit elements.

The paper is organized as follows. In Section 2 the capacitive RF MEMS switch modeled in this work is described and the description of the considered equivalent circuit model is given. The proposed inverse ANN modeling approach is presented in Section 3. The numerical results and discussion are given in Section 4. Section 5 contains concluding remarks.

2. Modeled Device

The RF MEMS switch analyzed in this work is a coplanar capacitive shunt switch. Top view of the fabricated switch is shown in Figure 1. a) and the cross-sectional view is shown in Figure 1. b). The switch is fabricated at FBK in Trento in an 8 layer silicon micromachining process [5].

The signal line below the bridge is made of a thin aluminium 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 switch has a structured membrane with a solid center part and a fingered part close to the anchors for adjusting electrical and mechanical parameters. The length of the fingered part, L_f, and solid part, L_s, can be changed in order to change the resonant frequency of the switch. The actuation mechanism used here is the electrostatic actuation. For a certain value of the voltage applied to the DC pads, the bridge comes down and touches a coplanar waveguide (CPW) centerline. The inductance of the bridge and the fixed capacitance between signal line and bridge form a resonant circuit to the ground. [14].

This process is 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 considered switch can be represented by a simplified equivalent circuit model, as it is shown in Figure 1c [15] It consists of the resistance *R,* the inductance *L* and the capacitance *C,* as well as two 50Ω CPW lines.

The switch resonant frequency can be calculated as:

$$f_{res} = \frac{1}{2\pi\sqrt{LC}} \,. \tag{1}$$

The switch capacitance in the membrane down-state, considered in this case, is calculated from the layout using the following expression [1]:

$$C = \frac{\varepsilon_0 \varepsilon_r A}{t_d}, \tag{2}$$

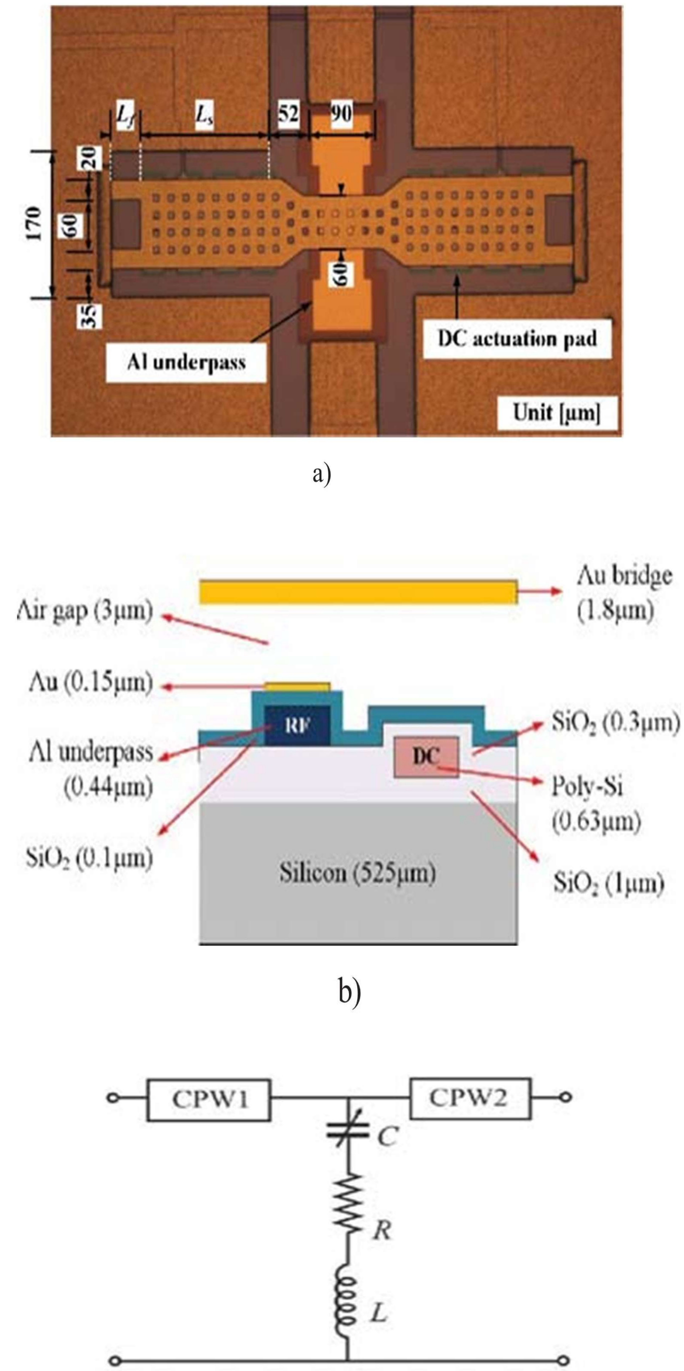

Figure 1. a) Top-view of the realized switch; b) schematic of the cross- section with 8 layers in FBK technology [5]; c) equivalent circuit of the RF MEMS switch RLC lumped element model

where ε_0 is the dielectric permittivity, ε_r is the relative dielectric permittivity, t_d is the distance between the two plates forming the capacitance and A is the surface of the plates orming the capacitance. As can be seen, the capacitance does not depend on the bridge lateral dimensions, i.e., it is constant with the changes of the bridge lateral dimensions. The other two elements, R and L, depend on the bridge lateral dimensions L_s and L_f.

During the design of switch, if a resonant frequency is given, which is usually the case, the inductance can be straightforwardly calculated from Eq. 1 as:

$$L = \frac{1}{4\pi^2 f_{res}^2 C} \tag{3}$$

The only parameter which is to be determined by optimizations in a circuit simulator is the resistance.

As far as the determination of the bridge lateral dimensions is concerned, they can be determined from the given inductance as explained in the following section.

3. Proposed Inverse ANN Model

As explained in the previous parts of the paper, the switch dimensions depend on the lateral dimensions, i.e., the bridge solid part (L_s) and the bridge fingered part (L_f). Once the switch inductance is calculated for the given resonant frequency, the lateral dimensions can be determined by ANN based models, as shown in Figure 2.

It should be mentioned that the inductance is not unique for different values of the dimensions, i.e., one inductance value matches several values of the bridge solid and fingered parts, but is unique to a combination of L_s and L_f. Having that in mind, it is not possible to find both L_s and L_f simultaneously by using a single ANN. Therefore, the two ANNs have to be used to determine L_s and L_f separately. One dimension has to be fixed to determine the other dimension. The ANN shown in Figure 2 a) is used to determine the bridge solid part for given value of the bridge fingered part and the ANN shown in Figure 2 b) is used to determine the bridge fingered part for the given bridge solid part.

To train the ANNs, it is necessary to calculate the equivalent circuit inductance for different combinations of the bridge lateral dimensions. This can be done in the full-wave simulators, where the S-parameters are calculated for different combinations of the bridge lateral dimensions. The resonant frequency is found for each case and is further used to calculate the equivalent circuit inductance. To have a complete equivalent circuit model, the resistance is determined by the optimizations in a circuit simulator. Moreover, an additional model for the resistance versus the lateral dimensions can be modeled by an ANN, as shown in [15].

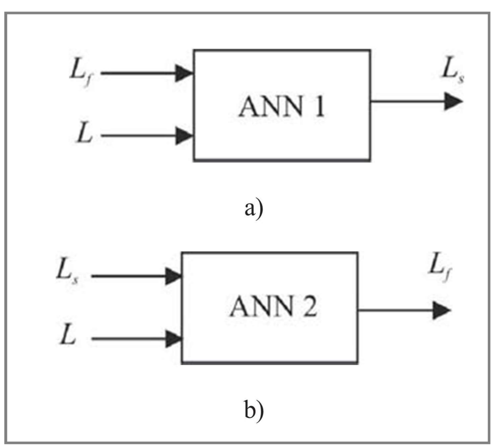

Figure 2. ANN inverse modeling for a) L_s , b) L_f

4. Numerical Results and Discussion

The training of the ANNs was performed by different training algorithms, and it was found that for the available data the best results in terms of learning (modeling accuracy for the training values) and generalization (modeling accuracy for the test values) were achieved by using the Bayesian regularization algorithm.

For all models, the ANNs with different number of hidden neurons were trained and compared, and the ones giving the best accuracy were chosen as the final ones. The accuracy was tested by estimating the absolute test error as well as the relative test error.

The training of ANN 1 was done using ten data samples, as shown in Table 1. The chosen ANN has two hidden layers of 25 neurons each. The test was done for the training data (Table I) and the test data (Table 2). In both cases, the absolute error is within the limit of 3gm, which is within the fabrication tolerances. The relative errors are less than 1%.

The ANN 2 was trained using the same combinations of the lateral dimensions as in the case of the ANN 1. The ANN showing the best accuracy has two hidden layers of 50 neurons each. The test statistics for the training and test input combinations are given in Table 3 and Table 4, respectively. The chosen ANN has two hidden layers of 50 neurons each. As in the previous case, the absolute error is within the limit of 31.tm for both training and testing samples. The relative error is except in a very few cases less than 1%.

The inverse modeling where the resonant frequency is taken as the ANN input instead the inductance can be seen in [12]-[15]. However, that alternative way to perform inverse modeling requires additional simulations (either in a full-wave EM simulator or preferably by using an ANN model trained to determine the resonant frequency for the given lateral dimension) to get more training data needed to achieve the acceptable absolute error limit of 3gm. The inverse model using inductance as the ANN input does not need any additional simulations and gives a good generalization with use of only 10 samples for training compared to 814 samples used for training of the inverse model using resonant frequency as shown in [12].

L_f [μm]	***L*** **[pH]**	**L_s - target [μm]**	**L_s - ANN [μm]**	**Abs. error [μm]**	**Rel. error [%]**
50	11.35	50	49.82	0.18	0.36
100	17.04	50	51.02	1.02	2.04
50	27.21	200	198.93	1.07	0.54
100	33.38	200	197.75	2.25	1.13
50	39.85	300	302.55	2.55	0.85
100	46.63	300	300.05	0.05	0.02
50	52.17	400	399.43	0.57	0.14
100	59.97	400	402.90	2.90	0.73
50	65.24	500	501.71	1.71	0.34
100	71.23	500	497.91	2.09	0.42

Table 1. Test Statistics for the Training Set for the ANN Model for LS Determination

L_f [μm]	L [pH]	L_s - target [μm]	L_s - ANN [μm]	Abs. error [μm]	Rel. error [%]
25	30.06	250	252.68	2.68	1.07
75	36.69	250	251.05	1.05	0.42
25	41.93	350	348.05	1.95	0.56
75	49.28	350	347.11	2.89	0.83

Table 2. Test Statistics for the test set for the ANN Model for L_S Determination

L_s [μm]	L [pH]	L_f - target [gm]	L_f - ANN [μm]	Abs. error [μm]	Rel. error [%]
50	11.35	50	49.96	0.04	0.08
50	17.04	100	100.06	0.06	0.06
200	27.21	50	50.29	0.29	0.58
200	33.38	100	99.39	0.39	0.39
300	39.85	50	50.25	0.25	0.50
300	46.63	100	100.76	0.76	0.76
400	52.17	50	48.76	1.24	2.48
400	59.97	100	100.16	0.16	0.16
500	65.24	50	51.42	1.42	2.84
500	71.23	100	99.05	0.95	0.95

Table 3. Test statistics for the test set for the ANN model for L_f determination

L_s [μm]	L [pH]	L_f - target [μm]	L_f - ANN [μm]	Abs. error [μm]	Rel. error [%]
250	30.06	25	23.93	1.07	4.28
250	36.69	75	74.31	0.69	0.92
350	41.93	25	22.72	2.28	9.12
350	49.28	75	73.41	1.59	2.13

Table 4. Test statistics for the test set for the ANN odel for L_f determination

5. Conclusion

Inverse ANN models developed to determine the bridge dimensions of RF MEMS switches could be very helpful in the RF MEMS switch design. They can be used for fast determination of the dimensions to get the desired inductance or resonant frequency. The inverse modeling approach proposed in this paper is combined with the equivalent circuit model. Namely, an ANN is used to determine one of the two bridge lateral dimensions, for the given value of the other lateral dimension and the equivalent circuit inductance calculated for the desired resonant frequency. According to the test statistics on the training data and on the test data not used for the model development, the difference between the determined and target values is smaller than the deviations from the nominal values which might appear during the fabrication process. Moreover, it was concluded that this approach enables achieving the same accuracy as the accuracy achieved with the previously proposed models, where the resonant frequency is used as an ANN input instead of the equivalent circuit inductance, but with a significantly smaller training data set.

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