Analysis of RF MEMS Capacitive Switches by Using Switch EM ANN Models

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***Abstract* — Artificial neural networks (ANNs) have appeared to be an alternative to the conventional models of RF MEMS switches. In this paper, neural models of an RF MEMS capacitive switch are developed and used for the electrical design of the switch. Namely, an ANN model relating the switch resonant frequency and the bridge dimensions is used to analyze efficiently the switch behavior with changes of bridge dimensions. Furthermore, it is illustrated how the developed model can be used for the determination of bridge dimensions in order to achieve the desired switch resonant frequency. In addition, application of a switch inverse ANN model for the determination of bridge dimensions is analyzed as well.**

***Keywords* — Artificial neural networks, resonant frequency, RF MEMS switch, design.**

I. Introduction

Artificial neural networks (ANNs) have been successfully applied for different modeling purposes in the field of electromagnetics and microwaves [1]-[5]. ANN models require a significantly shorter simulation time compared to simulations in the conventional electromagnetic (EM) simulators, keeping at the same time the same level of accuracy. Among other applications, ANNs have been applied to develop models of RF MEMS devices [6]-[10]. In this paper an RF MEMS capacitive switch is considered. RF MEMS switches are small mechanically reconfigurable components [11]-[14], which combine electrical and mechanical properties. Usually they are integrated as switching elements in bigger circuits like switch matrices, phase shifters or reflector-arrays. A single MEMS switch can be modeled with all available commercial full-wave software tools. However, the simulations can take a significant amount of time, what becomes a problem when it is necessary to repeat many simulations for different dimensions of the switch in order to estimate its behavior or to optimize the switch parameters. Recently, a neural model relating the RF MEMS switch resonant frequency to the dimensions of the switch bridge has been introduced [9]. It provides the determination of switch resonant frequency in a very short time. Therefore, it is convenient to be used for the efficient optimization of switch geometry. This paper presents results of the investigation how the developed model can be applied to the analysis of switch behavior as well as to the determination of switch dimensions avoiding additional optimizations during switch design. In addition, a switch inverse ANN model will be analyzed as well. The model consists of an ANN trained to determine one of the switch bridge dimensions, for known other dimensions and a desired resonant frequency [10].

The paper is structured as follows: a brief background of ANNs is given in Section II. Section III contains a description of the modeled device and the considered ANN models. The results and the discussion related to the application of the neural model for the switch design are presented in Section IV. The concluding remarks are given in Section V.

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II. Artificial Neural Networks

The ANNs used in this work are multilayer perceptron (MLP) artificial neural networks consisting of an input layer, an output layer as well as several hidden layers [1]. Each neuron is connected to all neurons from the next layer, while there are no connections between neurons within a layer. Neurons have assigned transfer functions, which are usually linear for input and output layer and sigmoid for hidden layers. Each connection between neurons is weighted.

An ANN is capable of learning the relationship among sets of input-output data (training sets) by adjusting its parameters, i.e. connection weights and thresholds of the neuron activation functions. For this purpose, several algorithms have been developed, such as the *backpropagation* algorithm or its modifications having a higher convergence, as *quasi Newton* or *Levenberg-Marquardt* algorithms [1].

The most important feature of ANNs is their generalization capability, i.e. the capability to provide a correct response even for the input values not presented to the ANN in the training process. In that way, the developed models can be used for a reliable prediction over a wide range of input parameters.

It should be noted that the number of input and output neurons is determined by a problem being modeled, but the number of neurons in the hidden layers is not a priori known and it is determined during the network training, by training the ANNs with different number of hidden neurons and choosing the one giving the best results.

III. Modeled Device and ANN model

The considered device is a CPW (Coplanar waveguide) based RF MEMS capacitive shunt switch, depicted in Fig. 1, fabricated at FBK in Trento in an 8-layer Silicon micromachining process [14]. The signal line below the bridge is made by 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, whose resonance 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 series resonance the circuit acts as a short circuit to ground. In a certain frequency band around the resonance frequency the transmission of the signal is suppressed. Therefore, the bridge dimensions (L_f, L_s) should be carefully determined in order to achieve the desired resonant frequency.

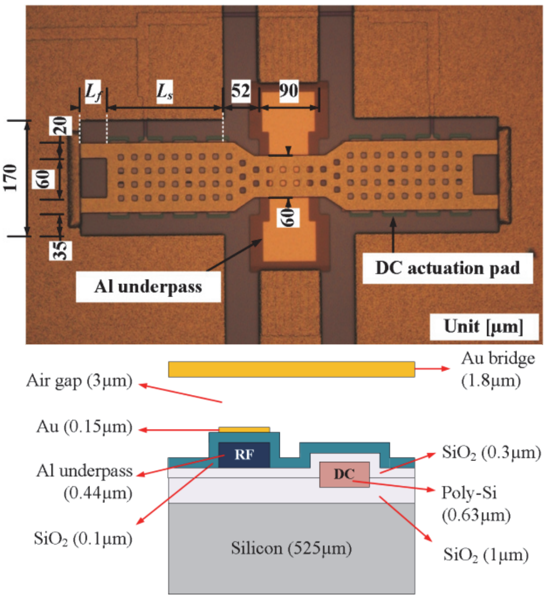


Fig. 1. Top-view of the realized switch and schematic of the cross-section with 8 layers in FBK technology [12].

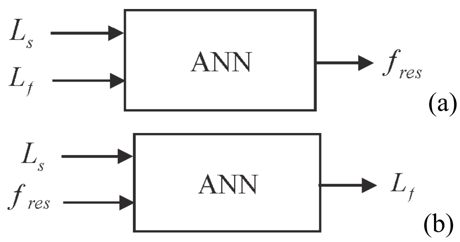


Fig. 2. RF MEMS switch ANN models: (a) resonant frequency model, (b) inverse EM model.

Having this in mind, an ANN model relating the mentioned bridge dimensions with the resonant frequency has been introduced. Namely, an ANN is trained to predict the resonant frequency for the given two geometry parameters L_s and L_f of the switch, as shown in Fig. 2 [9]. The used ANN is a multilayered ANN having two input and one output neuron.

As described in the next section, this ANN model can be used for fast determination of the resonant frequency, as the ANN response is practically instantaneous, enabling in that way efficient estimation of the switch behaviour with a change of bridge geometrical parameters and determination of the geometrical parameters to achieve a desired resonant frequency.

A switch inverse ANN model, shown in Fig. 2b [10], consists of an ANN trained to determine the switch fingered part length for a fixed switch solid part length and a desired resonant frequency. It has two input and one output neurons. Once developed, this model provides the determination of bridge dimensions directly without optimizations. In the next section it will be analyzed how to use this model to determine the switch bridge lengths if the total bridge length is fixed.

IV. Results and Discussion

A. *Resonant frequency neural model*

The ANN aimed for the resonant frequency determination of the considered switch was trained and validated by using the resonant frequency values calculated in a full-wave circuit simulator for different combinations of L_s and L_f. Namely, the training set contained the resonant frequency simulated for 17 different combinations of L_s and L_f. L_s was in the range: (50 - 500) μm and L_f in the range: (0 - 100) μm. Among the trained ANNs with different numbers of hidden neurons, the best results were obtained by the ANN having only one hidden layer containing five neurons. To illustrate the model accuracy, Table I shows the resonant frequency determined by the ANN model for several combinations of the geometrical parameters L_s and L_f not used for the training. The resonant frequency values simulated by the ANN are very close to the reference values calculated by full wave simulations (relative percentage error less than 1%), indicating a very good accuracy of the ANN model.

TABLE I
RF MEMS Switch Resonant Frequency

L_s (μm)	L_f (μm)	$f_{res\text{-}ANN}$ (GHz)	$f_{res\text{-}sim}$ (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

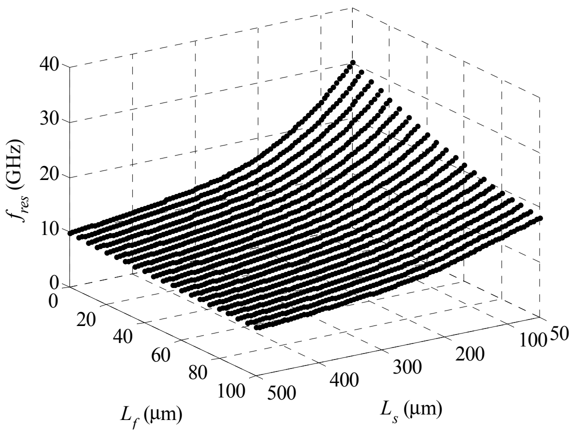


Fig. 3. Resonant frequency calculated by using the developed neural model.

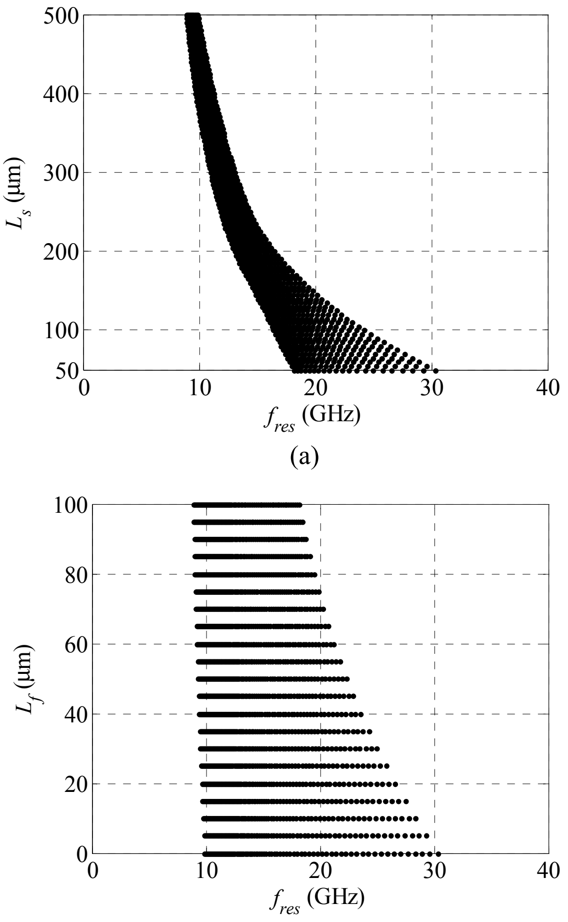


Fig. 4. Range of possible values of the resonant frequency for the considered range of bridge dimensions: (a) solid part length, (b) fingered part length.

To illustrate the efficiency of the proposed model, the resonant frequency was calculated by ANN model for the considered ranges of L_s and L_f: L_s (50 - 500) µm and L_f (0 - 100) µm and plotted in Fig. 3. It should be noted that the total simulation time was few seconds, which is significantly shorter compared to the electromagnetic simulator requiring several tens of minutes for calculating the resonant frequency for a single combination of bridge geometrical parameters. Moreover, optimization of the geometrical parameters to achieve the desired resonant frequency lasts around 2 hours in the electromagnetic simulator, while optimization performed by using mathematical expressions describing the ANN model (e.g. implemented in a circuit simulator) lasts several seconds, making the design process significantly shorter.

Although the simulation and optimization time can be reduced by applying the proposed model, it would be very useful for switch designers to have a way to determine the bridge dimensions for the desired resonant frequency without optimizations. With this aim, the authors of the paper worked on the development of an inverse ANN model which would calculate the considered bridge dimensions for the desired resonant frequency. However, it was not successful, as the input-output mapping is not unique, i.e. there are different combinations of bridge dimensions leading to the same value of the resonant frequency. Also, for the same reason it was not possible to develop a model which would find L_s and L_f for the desired resonant frequency if the total available length $L_t = L_s + L_f$ is given.

Here an alternative to the latter problem mentioned above is given. Namely, it will be demonstrated how the developed neural model can be used for the determination of bridge dimensions in order to achieve the desired resonant frequency for a given total length L_t, as often there are constraints on the available space where the bridge is to be placed. A short analysis of the plots given in Figs. 4 and 5 would help in understanding the proposed method. Namely, the same resonant frequency data shown in Fig. 3, are given in Fig. 4, where the bridge dimensions are plotted versus the resonant frequency. It can be seen that for the dimensions from the considered ranges the resonant frequency from 8 to 30 GHz, roughly, can be achieved. Also, for each resonant frequency there is a range of possible L_s and L_f values, meaning that not any value of the total length could be paired with an arbitrary resonant frequency value. Having in mind the considered ranges of L_s and L_f, the total length values were considered within the range (50 - 600) µm. Further, for different values of percentage, $p = 100 \cdot L_s / L_t$, and L_t in the mentioned range (with a step of 50 µm), L_s, L_f and the corresponding resonant frequencies were calculated and shown in Fig. 5. As the calculated L_s and L_f values can be out of the initial ranges (e.g. if L_t is 500 µm, for percentage 20% the corresponding L_s is 100 µm and L_f is 400 µm, which is out of the considered L_f range), the values corresponding to the considered L_s and L_f ranges are colored red. Therefore, for each desired frequency the right combination of L_s and L_f can be simply taken from the plots corresponding to the given L_t. To illustrate this further, in the following example the total length should be 400 µm. L_s and L_f were calculated for different percentage values and the obtained values are plotted versus f_{res}, Fig 6.

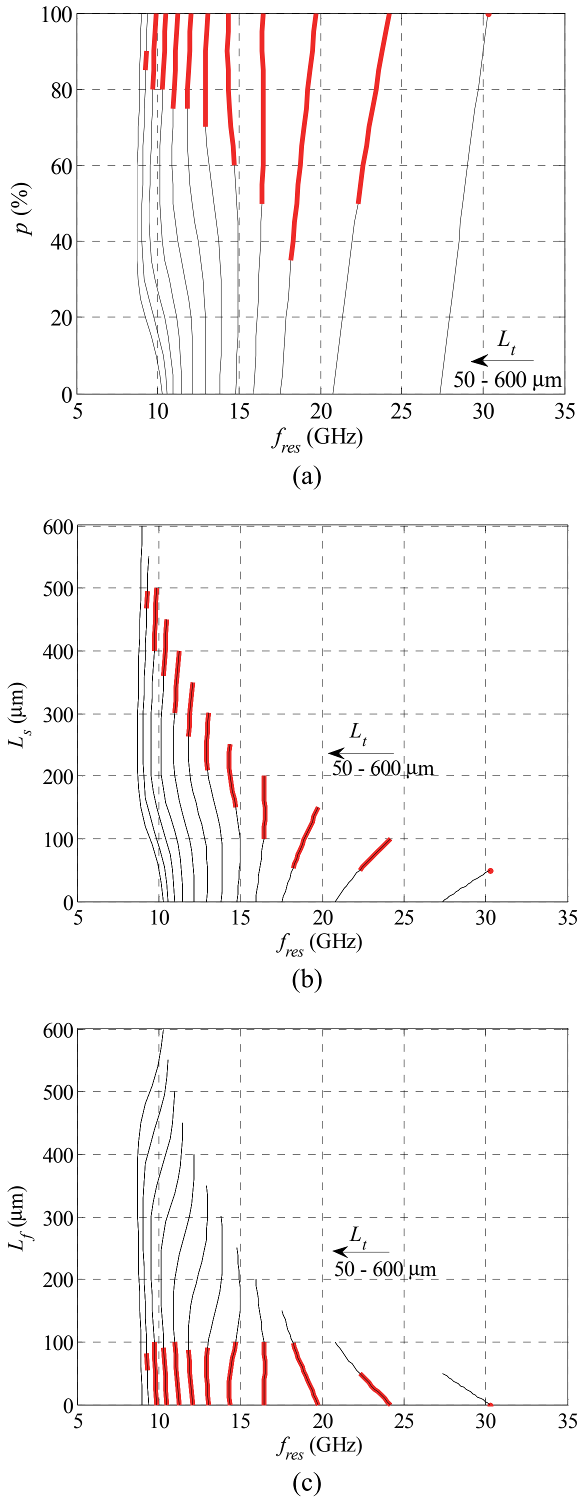


Fig. 5. Possible values of bridge dimensions versus the resonant frequency for different values of total length L_t versus: (a) percentage, (b) L_s, (c) L_f

As in the previous case, red and blue colored lines correspond to the considered ranges of dimensions. It can be seen that possible resonant frequencies that could be achieved for this total length are roughly, from 10.8 GHz to 12.2 GHz. If the desired frequency is 11 GHz, L_s is 310 μm and L_f is 90 μm.

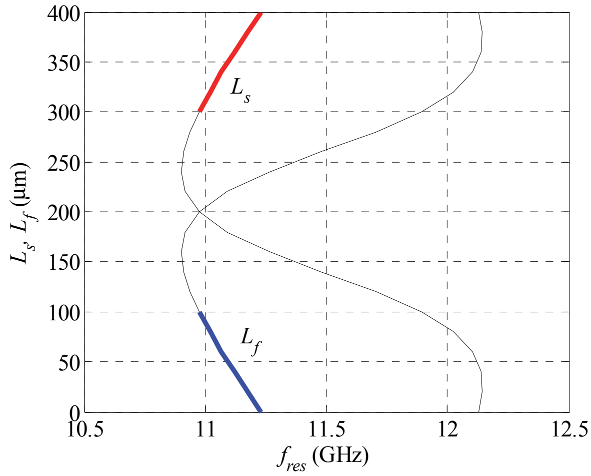


Fig. 6. Possible values of bridge dimensions versus the resonant frequency for the total length L_t=400 μm

B. *Inverse ANN Model*

The same data obtained in EM simulators used for the training of the resonant frequency neural model can be used as the training data for the inverse neural model. However, in order to obtain more training data to ensure good accuracy of the inverse model, but not increasing the time needed for additional simulations, the training data for the inverse model was obtained by the resonant frequency neural model described above. The training data was in the range corresponding to the data shown in Figs. 3 and 4. Among the trained ANNs, the best one was the ANN having two hidden layers each composed of 15 neurons. The training set consisted of 841 samples. More details about the inverse model development and verification can be found in [10]. As shown in [10], the accuracy of the L_f prediction is about 3%, with the absolute difference of the predicted and expected values less than 3 μm, which is close to fabrication tolerances, confirming the accuracy of the model.

Once this model is developed, the L_f can be determined instantaneously, by calculating ANN response for given values of L_s and f_{res}. Similarly to the previous analysis, it will be analyzed how the developed neural model can be used for the determination of bridge dimensions for a given total length L_t in order to achieve the desired resonant frequency. First, one should be sure if the desired resonant frequency can be achieved with a bridge of the chosen length. In order to make such a check, a plot shown in Fig. 7 can be used. It was made by using the same data shown in Fig. 3, where L_t was calculated as $L_t = L_s + L_f$. As an illustration, frequency of 20 GHz can be achieved only with the devices having the bridge total length of, roughly, 130 μm to 150 μm. After verification that the desired combination of L_t and f_{res} is physically meaningful, L_s and L_f can be easily found graphically. Namely, they are determined by the intercept point of the following functions:

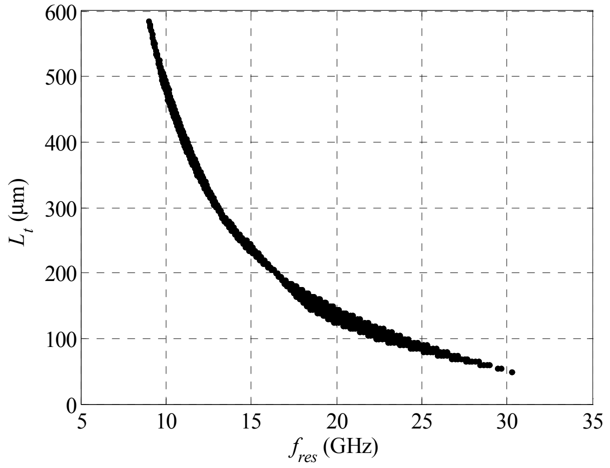
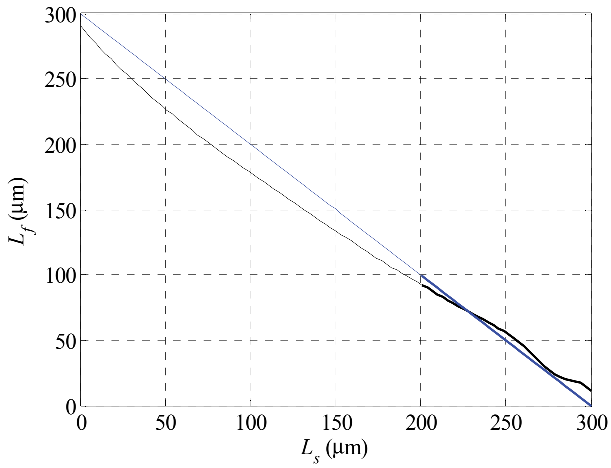
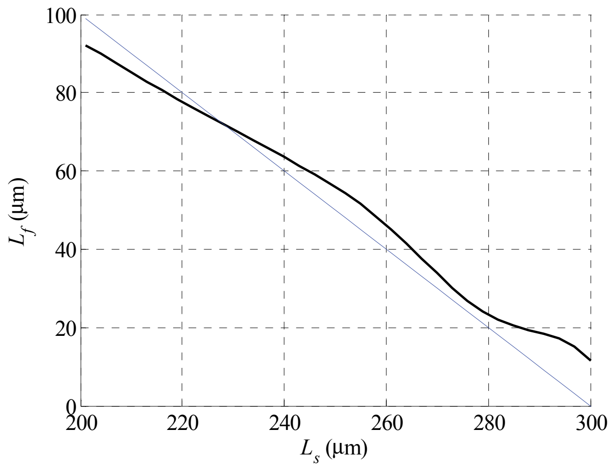


Fig. 7. Bridge total length versus resonant frequency in the considered range of bridge dimensions.



(a)



(b)

Fig. 8. L_s and L_f determination for the bridge total length L_t=300 μm.

$L_f = f_{inv\_ANN}(L_s, f_{res})$ obtained by the inverse neural model and $L_f = L_t - L_s$. In both functions L_s should be varied from 0 μm to L_t. For instance, let the desired f_{res} be 13 GHz and the desired L_t 300 μm. For L_s from 0 μm to 300 μm, L_f is calculated by using the inverse model and plotted in Fig. 8a as a black line. The function $L_f = L_t - L_s$ is a linear function plotted as a blue line. The plot from Fig. 8a is zoomed around the intercept point and shown in Fig. 8b, i.e., Fig. 8b shows the physically possible values (which are represented in Fig. 8a as thicker parts of plotted lines). The intercept point corresponds to the following dimensions of the bridge: L_s =228 μm and L_f=72 μm.

V. Conclusion

This paper describes the applications of the developed neural models of electrical behaviour of RF MEMS capacitive switches. First, a resonant frequency ANN model relating the switch resonant frequency to switch dimensions has been analyzed. It has been applied not only for efficient accurate simulations and optimizations of switch behavior, but also for the determination of switch dimensions for the given resonant frequency. Further, determination of the bridge fingered part by the inverse ANN model has been analyzed. The model provides accurate and instantaneous determination of the length of the fingered part. Applicability of both models for the determination of bridge dimensions for a desired frequency and for a given total length of the bridge has been illustrated. Several recommendations related to applications of these models have been given. As the considered bridge dimensions influence, besides the resonant frequency, also the value of the necessary actuation voltage, further research will be devoted to modeling the switch mechanical characteristics.

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