FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 29, N° 2, June 2016, pp. 177 - 191
DOI: 10.2298/FUEE1602177M

ARTIFICAL NEURAL NETWORKS IN RF MEMS SWITCH MODELLING

Zlatica Marinković[1], Vera Marković[1], Tomislav Ćirić[1], Larissa Vietzorreck[2], Olivera Pronić-Rančić[1]

[1]University of Niš, Faculty of Electronic Engineering, Niš, Serbia
[2]TU München, - Lehrstuhl für Hochfrequenztechnik, München, Germany

Abstract. *The increased growth of the applications of RF MEMS switches in modern communication systems has created an increased need for their accurate and efficient models. Artificial neural networks have appeared as a fast and efficient modelling tool providing similar accuracy as standard commercial simulation packages. This paper gives an overview of the applications of artificial neural networks in modelling of RF MEMS switches, in particular of the capacitive shunt switches, proposed by the authors of the paper. Models for the most important switch characteristics in electrical and mechanical domains are considered, as well as the inverse models aimed to determine the switch bridge dimensions for specified requirements for the switch characteristics*.

Key words: *actuation voltage, artificial neural networks, resonant frequency, RF MEMS, switch*

1. INTRODUCTION

Modern communication systems rely to a great extent on new high performance RF and microwave devices and components that enable miniaturization of components according to the demand of integrating more and more functionalities by reducing the overall size of the system at the same time. RF MEMS (Micro Electro Mechanical systems) are novel components which are able to meet the mentioned requirements [1].

RF MEMS components and devices exploit mechanically movable parts and thus enable a change of topology. One of the first examples developed in 1995 [2, 3] was an electrostatically actuated RF MEMS shunt switch where the ground of the coplanar waveguide is connected by a very thin membrane. If a DC voltage is applied between ground and signal line, the membrane is pulled down by the electrostatic force and thus it shortens the signal line. Since these first developments, many different components based on MEMS switches have been introduced, like phase-shifters, reconfigurable antennas, matching networks, switch matrices, tunable filters, etc. [4-9]

Received September 29, 2015
Corresponding author: Zlatica Marinković
University of Niš, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš, Serbia
(e-mail: zlatica.marinkovic@elfak.ni.ac.rs)

RF MEMS switches allow multiband operation due to their ability to reconfigure its topology. Also, they have several advantages compared to their electronic counterparts, like PIN diode or MESFET switches [10]-[12], such as: low insertion loss, high isolation, small size, high linearity and excellent compatibility with microwave and mm-wave circuits. Because of those significant advantages, RF MEMS switches are of growing interest for use in various communication systems, primarily in satellite and mobile communication systems.

Current research of RF MEMS switches is mostly concentrated on various new structures, new materials or processes in devices [13]-[16], while optimization analysis of MEMS devices lacks enough study. A standard approach to obtain RF MEMS switch electrical characteristics is to use full-wave numerical methods in electromagnetic (EM) simulators. However, as it is also necessary to determine mechanical characteristics, simulations in mechanical simulators should be included during the design and simulation as well. Although these methods provide the necessary accuracy, they are generally limited to a single analysis for a specific structure, and their computational overhead (running time, memory) becomes extensive when a number of simulations with different mesh properties are needed [17].

An alternative approach to modelling and designing RF MEMS devices is based on artificial neural networks (ANNs). ANNs can be considered as a great fitting tool, i.e. they have the ability to learn the dependence between two sets of data and to generalize, which means to give a correct response to inputs not used in the learning process. They give response almost instantaneously, retaining the accuracy of the standard EM and mechanical simulators. Owing to these abilities, ANNs have found a lot of applications in different fields, among others in RF and microwaves. This paper is devoted to applications of ANNs for modelling and design of RF MEMS switches.

As far as RF MEMS devices are concerned, ANNs have been applied as a modelling tool about for a decade [17-25]. They have mostly been applied for modelling the device membrane characteristics. Several publications refer to neural modelling of RF MEMS switches [17, 20, 23-25]. In most of the referred applications, ANNs were exploited to model dependence of the switch scattering (S-) parameters and/or switch resonant frequency on the dimensions of membrane and frequency. Almost all of them refer to switches which have a simple rectangular membrane. In this paper a capacitive switch with a more complex membrane is considered.

The paper is organized as follows. After Introduction, in Section II a short description of neural networks is given. The capacitive RF MEMS switch modeled in this work is described in Section III. ANN models of switch characteristics, as well as corresponding numerical results and discussions, are presented in Section IV. Section V contains description of RF MEMS switch inverse ANN models, the modelling results and the discussion. Finally, the main concluding remarks are given in Section V.

2. ARTIFICIAL NEURAL NETWORKS

All neural models presented in this work are based on the multilayer perceptron (MLP) neural networks. An MLP ANN consists of basic processing elements (neurons) grouped into layers: an input layer, an output layer, as well as several hidden layers [26].

Each neuron is connected to all neurons from the adjacent layers. Neurons from the same layer are not mutually connected. Each neuron is characterized by a transfer function and each connection is weighted. The ANNs exploited in this work have linear transfer function for neurons from the input and output layer and sigmoid transfer function for the hidden neurons. An ANN learns the relationship among sets of input-output data (training sets) by adjusting the network connection weights and thresholds of activation functions. There are a number of algorithms for training of ANNs. The most frequently used are backpropagation algorithm and its modifications, as the Levenberg Marquard algorithm [26], 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., the ability to generate the 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 modelling in the field of RF and microwaves [26-36]. As examples, ANNs could be used as an alternative to time-consuming electromagnetic simulations [26-28, 30] or an alternative to the conventional modelling of microwave devices [25, 27, 30, 32, 35, 36].

In the present work, the accuracy of ANN learning and generalization was tested by calculating average test error (ATE), worst case error (WCE) and Pearson Product-Moment correlation coefficient (r) [26]. Having in mind that it is not possible to determine the number of hidden neurons, in this work for each developed ANN, ANNs with different number of hidden neurons in one or two hidden layers were trained. The network with the best test results was chosen as the final model. When reporting the ANN structure of the final models, in this paper the following notation is used: ANN denoted with N-H1-H2-M, has N input neurons, H1 and H2 neurons in the first and second hidden layer, respectively, and M output neurons; ANN denoted with N-H1-M, has N input and M output neurons and only one hidden layer with H1 neurons.

3. Modeled Device

The considered device is a CPW (Coplanar waveguide) based RF MEMS capacitive shunt switch (see Fig. 1) fabricated at FBK in Trento in an 8-layer Silicon micromachining process [37]. 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. The bridge can be closed by applying an actuation voltage of around 45 V. The actuation voltage is determined as the instant voltage applied to the DC pads when the bridge comes down and touches a CPW 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 a 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].

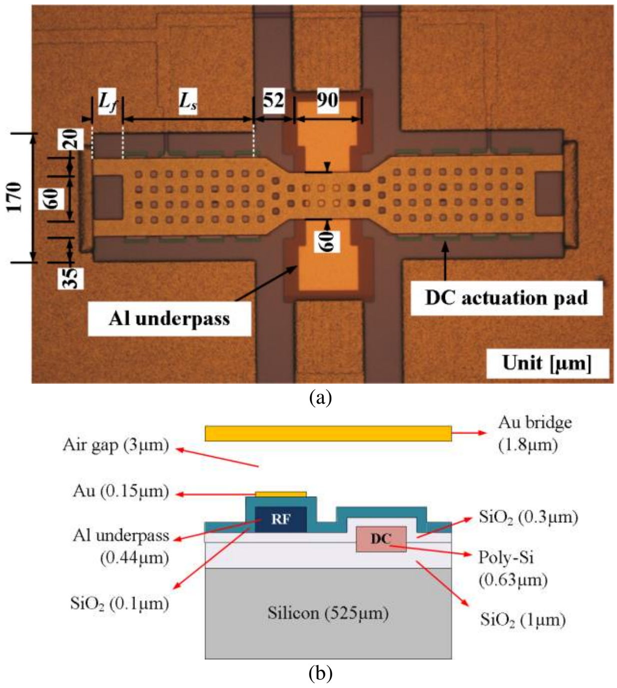


Fig. 1 Top-view of the realized switch (a) and schematic (b) of the cross-section with 8 layers in FBK technology [37]

4. ANN Models of Switch Characteristics

As mentioned in the introductory section, simulations of an RF MEMS switch characteristics in standard EM and mechanical simulators are time consuming, which is especially important when it is necessary to repeat simulations during the design and optimization of the switch characteristics. Similarly to the approaches presented in the literature, the authors of this paper have developed neural models of switch electrical and mechanical characteristics, in particular the neural models of S-parameters, resonant frequency and actuation voltage, as shown in Figs. 2 and 3.

An RF MEMS switch is a symmetric reciprocal device, i.e., $S_{22} = S_{11}$ and $S_{12} = S_{21}$, therefore only parameters S_{11} and S_{21} were modeled. The ANN model of each modeled S-parameter consists of two ANNs, both having three inputs corresponding to the bridge lateral dimensions, L_s and L_f, and frequency, f, whereas the outputs correspond to the magnitude and phase of the modeled parameter, $|S_{ij}|$ and $\angle S_{ij}$, respectively. With the aim to train the ANNs, it is necessary to simulate the S-parameters for several bridge sizes (i.e. for different values of the bridge lateral dimensions) in a full-wave EM simulator. A properly trained ANN gives responses which are very close to the response of the full-wave EM simulator but in a shorter time, as the ANN response is almost instantaneous. By using the developed model, analysis and optimizations of the switch dimensions can be done much faster than in the standard way.

As far as the resonant frequency is concerned, the ANN model consists of one ANN with two inputs corresponding to L_s and L_f , and one output corresponding to the resonant frequency (see Fig. 2b). The data for the ANN training consists of several resonant frequencies corresponding to different bridge sizes, and can be acquired by determining the resonant frequency in a full-wave EM simulator, or by using the neural model of the parameter S_{21}. Like the above mentioned model, this model enables a quick estimation of the switch resonant frequency and optimization of the dimensions to obtain the desired resonant frequency.

The model of the switch actuation voltage has the same structure as the resonant frequency model. Namely, it has two inputs and one output, corresponding to the bridge lateral dimensions and actuation voltage, respectively, as shown in Fig. 3. As in the previous cases, the training data were obtained in a standard simulator able to calculate the switch mechanical properties. The gain in simulation time is the most significant in this case, as simulations in commercial mechanical simulator took much more time than the simulations of the electrical parameters in a full-wave EM simulator.

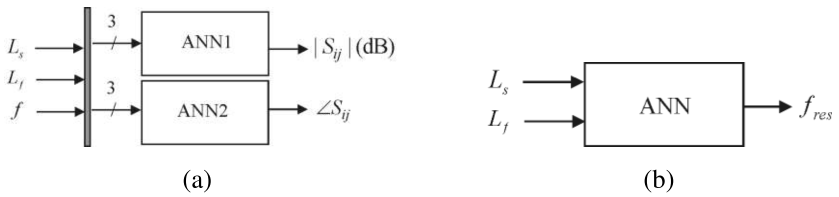


Fig. 2 ANN models of the switch electrical characteristics:
(a) S-parameters; (b) resonant frequency

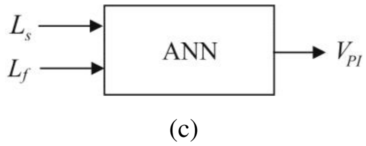


Fig. 3 ANN model of the switch actuation voltage

4.1. Numerical results

All ANN models described above were developed for the considered switch [38, 39]. For development of the models of S-parameters and resonant frequency, the S-parameters for several different combinations of the switch lateral dimensions were simulated in the full-wave EM simulator, ADS momentum [40], and the corresponding resonant frequencies were determined. The data referring to 23 differently sized bridges were used for the model development, whereas the data referring to 17 bridges different than the training ones were used for validation of the models. The S-parameters used for the model development were simulated in 401 frequency points up to 40 GHz. For each ANN model, ANNs with different number of hidden neurons were trained and the ANNs listed in Table 1 were chosen as the final models.

Table 1 Final ANN models for the switch electrical and mechanical characteristics with the number of training samples

Parameter	ANN model	Number of training samples
$\|S_{11}\|$	3-8-6-1	23 x 401
$\angle S_{11}$	3-10-10-1	23 x 401
$\|S_{22}\|$	3-8-8-1	23 x 401
$\angle S_{22}$	3-10-10-1	23 x 401
f_{res}	2-5-1	23
V_{PI}	2-8-1	30

Validation of the ANN models has shown that they produce the values which are very close to the values obtained by using the EM simulator. As an illustration, in Fig. 4 the insertion loss ($|S_{21}|$ in dB) and the return loss ($|S_{11}|$ in dB) are shown for the device having the bridge with lateral dimensions L_s = 350 µm and L_f= 75 µm. A very good agreement of the parameters generated by using the developed ANN models with the EM simulations can be observed. This is especially important, as the data referring to this device was not included in the training set, proving that the ANNs achieved a good generalization.

As far as the resonant frequency is concerned, the maximum difference between the modeled and the reference values for the test devices is less than 1%, which can be considered very good. Another illustration of the achieved accuracy of the resonant frequency ANN model is the scattering plot given in Fig. 5 showing very good agreement of the values obtained by the ANN model and the reference values calculated in the EM simulator for six considered test devices. More details about development and validation of the ANN models of the electrical characteristics can be found in [38, 39].

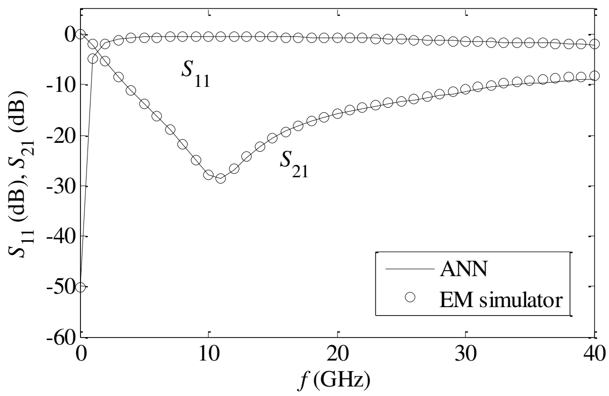


Fig. 4 Insertion and return losses for the tested device (L_s = 350 µm and L_f= 75 µm)

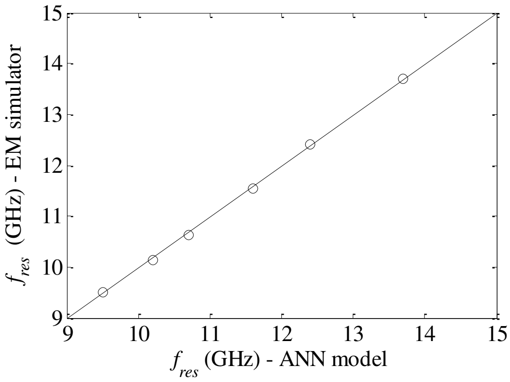


Fig. 5 Resonant frequency scattering plot for six test devices

The data used for training and validation of the neural model for the switch actuation voltage, shown in Fig. 3, were obtained in the mechanical simulator COMSOL Multiphysics [41]. In total, 39 data samples (pairs of lateral dimensions and the corresponding actuation voltages) were used, thereof 30 for the ANN training and 9 for the ANN model validation. The best ANN has one hidden layer with 8 neurons, as listed in Table 1. The validation results shown in Table 2 confirm that this model also has very good generalization abilities, as the maximum error for the test devices not used for the ANN training is around or less than 1%, i.e., less than 0.5 V. More details about development and validation of this model can be found in [42, 43].

Table 2 Actuation voltage for the test devices

L_s (µm)	L_f (µm)	V_{PI_target} (V)	V_{PI_sim} (V)	Abs. error (V)	Rel. error (%)
150	25	55.6	55.58	0.02	0.01
150	65	43	43.45	0.45	1.10
250	25	33.3	33.16	0.14	0.40
250	65	28.2	28.21	0.01	0.03
350	10	25.2	25.32	0.12	0.47
350	25	23.8	23.74	0.06	0.25
350	65	21.1	20.99	0.11	0.54
350	75	20.5	20.45	0.35	0.17
450	65	16.9	16.80	0.10	0.57

4.2. Discussion

As already mentioned, the developed models of the RF MEMS switch characteristics give responses instantaneously. Having in mind that they give the responses with the accuracy close to the accuracy of the calculations in standard EM and/or mechanical simulators, they are very convenient to be used for further analyses and optimizations of the considered switch. The mathematical expressions describing the developed ANNs can be easily implemented within the standard simulators by means of blocks dealing with variables and expressions, or can be used separately in different (mathematical) software packages. As an example, optimization of the bridge lateral dimensions for the given requirements for S-parameters in a desired frequency band lasts less than a second when performed by using the neural model implemented in the ADS circuit simulator, which is significantly faster than the optimization in the full wave simulator (ADS momentum), which lasts around 2 hours [39].

This advantage is even more evident in the case of the mechanical characteristics modelling. Namely, the calculation of switch actuation voltage versus the bridge lateral dimensions (plotted in Fig. 6), lasts few seconds in the MATLAB environment by using the developed ANN model, whereas the mechanical simulator requires several tens of minutes to determine the actuation voltage for a single combination of the bridge geometrical parameters. Optimization of the switch bridge dimensions based on the ANN model lasts several seconds, unlike the optimizations in the mechanical simulators lasting for hours.

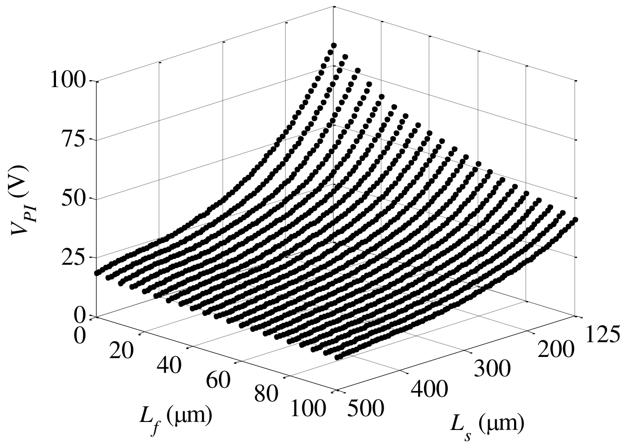


Fig. 6 Actuation voltage calculated by using the ANN model [42]

The developed ANN models can be efficiently used to study the behaviour of the device when the bridge size is changed, either intentionally, with the aim to optimize the device characteristics, or due to the deviation of the dimensions in the device fabrication process. The analyses done in [44] for the resonant frequency and in [45] for the actuation voltage show that when the dimension changes are within the fabrication tolerances (which are for the considered device up to +/– 3 μm) the changes in the actuation voltage and the resonant frequency can be considered as acceptable. For instance, maximum changes of the resonant frequency for several arbitrary chosen devices when both dimensions were changed in the range +/– 3 μm, with the step of 1 μm are shown in Table 3 [44]. It can be seen that maximum deviation of the resonant frequency is 1.5%, with the maximum absolute change of 0.24 GHz.

Table 3 Resonant frequency test results for simultaneous changes of L_s and L_f up to +/- 3 μm

L_s (μm)	L_f (μm)	Max $\lvert\Delta f_{res}\rvert$ (GHz)	Max $\lvert\Delta f_{res}/f_{res}\rvert$ (%)
200	20	0.24	1.5
200	50	0.20	1.4
200	80	0.17	1.3
300	20	0.13	1.1
300	50	0.12	1.0
300	80	0.11	0.1
450	20	0.08	0.8
450	50	0.07	0.7
450	80	0.06	0.6

5. RF MEMS SWITCH INVERSE ANN MODELS

As illustrated in the previous section, the developed neural models of the electrical or mechanical characteristics of RF MEMS switches can significantly speed up the analysis and design of these switches. However, the time needed for the optimization of switch dimensions can be further reduced if the inverse neural models of the switch characteristics versus dimensions are used. Namely, it would be very useful to develop models that could predict both of the lateral dimensions of the switch bridge for the given resonant frequency or/and actuation voltage. However, this is not possible, as the inverse functions of the resonant frequency and actuation voltage dependence on the bridge dimensions are not unique, which means that several combinations of the lateral dimensions result in the same resonant frequency or actuation voltage. The authors of the paper proposed inverse models where one of the dimensions is fixed, and the other is determined by an ANN, as shown in Fig. 7 [39, 43, 46, 47].

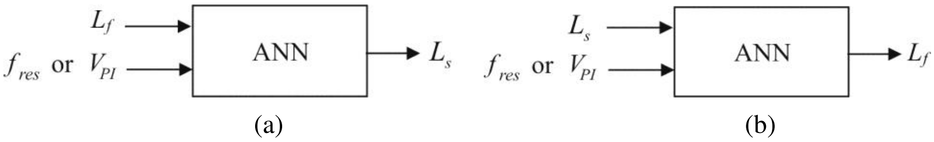


Fig. 7 Inverse ANN models for the switch electrical (or mechanical) characteristics: (a) L_s (b) L_f

Namely, the proposed inverse ANN models of the switch electrical (or mechanical) characteristics consist of ANNs with two input neurons: one corresponding to the fixed lateral dimension (L_f in Fig. 7a and L_s in Fig. 7b) and the other to f_{res} in the case of electrical inverse model, or to V_{PI} in the case of mechanical inverse model, and one output neuron corresponding to the dimension being determined (L_s in Fig. 7a and L_f in Fig. 7b).

However, during the design of an RF MEMS switch one may have a need to optimize the dimensions to meet the desired resonant frequency and the actuation voltage simultaneously. That could be complex as the EM simulations and simulations of the mechanical characteristics are performed in different software packages. Therefore, the authors proposed inverse electromechanical models, which calculate one of the lateral dimensions for given both, the resonant frequency and the actuation voltage. For the same reasons as in the case of separate electrical and mechanical inverse models, it is not possible to develop a model that would determine both dimensions at the same time. Therefore, the exploited ANNs have three inputs and one output, as shown in Fig. 8.

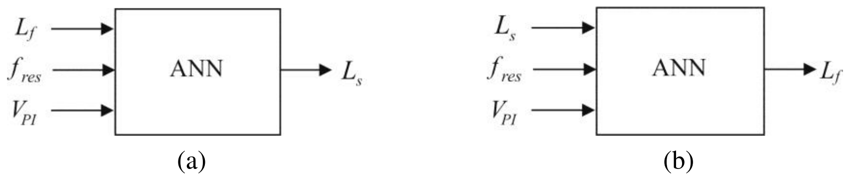


Fig. 8 Inverse electro-mechanical ANN models: (a) L_s (b) L_f

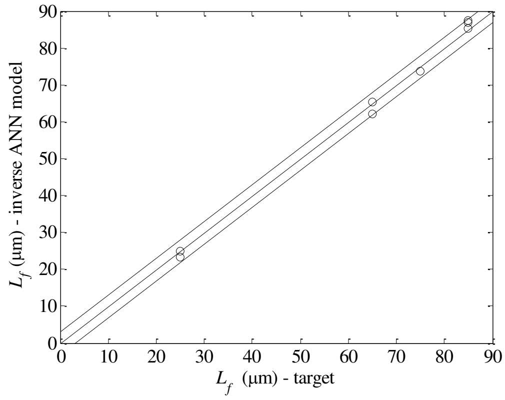
For both types of the inverse models, separate electrical and mechanical or electro-mechanical ANN model, the data for training the ANNs is obtained by calculating the resonant frequency or/and the actuation voltage for several combinations of the lateral dimensions. This can be done in standard simulators, or alternatively by the previously developed neural models aimed at calculating the resonant frequency and actuation voltage for the given dimensions (let us call them the direct models). Once the inverse models are trained, the determination of the desired dimension is done directly without optimization.

5.1. Numerical results

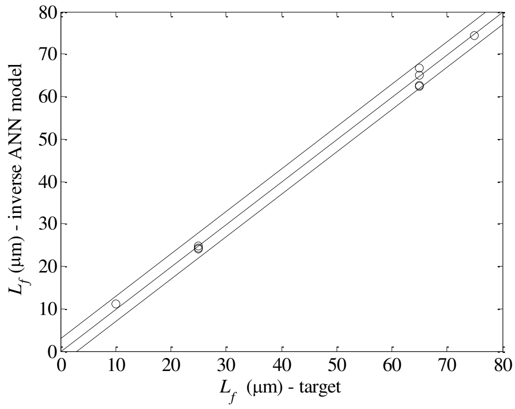
The proposed inverse ANN models were developed for the RF MEMS switch considered in this work. Due to behaviour of the inverse characteristics of the considered devices, it appeared that the data used for the development of the direct models of the resonant frequency and actuation voltage were not sufficient to train the inverse ANN models with the satisfying accuracy, as the modelling error was higher than tens of percent in some parts of the input space [39, 43, 46]. Therefore, to acquire more training data in these critical parts of the input space, the developed direct neural models were used for generating more training samples. The ANNs showing the best performance for each model are listed in Table 4, together with the number of training samples. To illustrate the accuracy of the inverse modelling, in Fig. 9 a comparison of the determined L_f and its target value is plotted in the form of scatter plots. Fig. 9a refers to the electrical inverse model and Fig. 9b to the mechanical inverse model. It can be observed that the deviation of the L_f value is within the boundaries of +/-3 μm, indicating very good prediction abilities of the proposed model. Similar results were obtained for prediction of L_s.

Table 4 Final ANN models for the switch electrical and mechanical characteristics with the number of training and test samples

Inverse Model	ANN model	Number of training samples
Electrical L_f	2-15-15-1	814
Electrical L_s	2-15-15-1	814
Mechanical L_f	2-25-25-1	961
Mechanical L_s	2-4-6-1	961
Electro.Mech. L_f	3-10-20-1	4131
Electro.Mech. L_s	3-20-10-1	4131



(a)



(b)

Fig. 9 Inverse modelling of L_f : (a) electrical inverse model, (b) mechanical inverse model

The inverse electro-mechanical models gave similar accuracy as the separate electrical and mechanical models, which can be seen from the following analysis, where the inverse electromechanical model for determining the fingered part length (shown in Fig. 8b) is considered. The influence of the determination of L_f to changes of the resonant frequency (desired value 12 GHz) and the actuation voltage (desired value 25 V) were calculated and shown in Tables 5 and 6, respectively [48]. Namely, for the L_s values from 280 to 340 µm, and the desired f_{res} and V_{PI}, the value of L_f is calculated (L_{f_inv}). Further, the calculated L_f value is used to determine the resonant frequency (Table 5) or the actuation voltage (Table 6) with the direct ANN models for f_{res} and V_{PI}, respectively, and these values were compared with the desired values. The corresponding absolute errors (AE) and relative errors (RE) are given in Tables 5 and 6 as well. It can be seen that the relative errors are less than 2%, which can be considered as good.

Table 5 RF MEMS switch inverse modelling results: f_{res} [48]

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	71.350	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 6 RF MEMS switch modelling results: V_{PI} [48]

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

5.1. Discussion

The results shown above confirm the accuracy of the determination of the lateral dimensions of the bridge for the given requirements related to the resonant frequency and/or the actuation voltage. The deviation in the dimension prediction is in the order of fabrication tolerances, confirming also the accuracy of modelling. The developed inverse models provide a very fast straightforward calculation of the bridge dimensions. Opposite to the direct models, which are valid in the range of the dimensions used for the ANN model development, although the inverse models give response for all the inputs falling between minimum and maximum values of input values used for training, they are valid only in the ranges of input values which are physically meaningful. This means that before choosing an input combination for an inverse model, it should be checked if the chosen combination is physically meaningful. This can be efficiently checked from two-dimensional plots input dimension - resonant frequency (and/or actuation voltage, depending on the inverse model used) which can be plotted by using the direct ANN models [49, 50].

Another challenge in bridge dimension optimization is how to determine the bridge lateral dimensions when total length of the bridge is given. Since the desired dependence is not unique, as it is case for all mentioned inverse models, such direct model is not possible to be realized with ANNs. However, the developed ANN based direct and inverse models can be used as a solution. The interested readers can find more details about it in [49- 51].

6. CONCLUSION

RF MEMS switches have seen increasing applications in the field of microwave control, therefore, the design of the circuits containing RF MEMS switches require the presence of the reliable models. Artificial neural networks have appeared as an efficient alternative to standard commercial full-wave EM simulators and mechanical simulators providing similar accuracy but with significantly lower computational cost. This paper gives an overview of the neural models of capacitive shunt RF MEMS switches.

Despite the fact that the development takes a certain time, as it is necessary to obtain the training data by using the standard simulation methods and to train the ANN models (a few minutes per a trained ANN), efficiency and speed in giving response make the ANN models very convenient for modelling and optimization of electrical and mechanical characteristics of RF MEMS switches.

Acknowledgement: *The authors would like to thank FBK Trento, Thales Alenia Italy, CNR Rome and University of Perugia, Italy for providing RF MEMS data. This work was funded by the bilateral Serbian-German project "Smart Modeling and Optimization of 3D Structured RF Components" supported by the DAAD foundation and Serbian Ministry of Education, Science and Technological Development. The work was also supported by the projects TR32052 and III-43012 of the Serbian Ministry of Education, Science and Technological Development.*

REFERENCES

[1] G. M. Rebeiz, *RF MEMS Theory, Design, and Technology*. New York: Wiley, 2003.
[2] C.L. Goldsmith, Z. Yao, S. Eshelman, and D. Denniston, "Performance of Low-Loss RF MEMS Capacitive Switches," *IEEE Microwave Guided Wave Lett*., vol. 8, pp. 269-271, August 1998.
[3] G. M. Rebeiz, J. B. Muldavin, "RF MEMS Switches and Switch Circuits," *IEEE Microw. Mag.*, vol. 2, no. 4, pp. 59-71, December 2001.
[4] S. A. Figur, E. Meniconi, B. Schoenlinner, U. Prechtel, R. Sorrentino, L. Vietzorreck, V. Ziegler, "Design and Characterization of a Simplifed Planar 16 x 8 RF MEMS Switch Matrix for a GEO-Stationary Data Relay", In Proceedings of European Microwave Conference, 2012.
[5] S. Montori, E. Chiuppesi, P. Farinelli, L. Marcaccioli, R. V. Gatti, R. Sorrentino, "W-band beam-steerable MEMS-based Reflectarray", *International Journal of Microwave and Wireless Technologies*, vol. 3, no. 05, pp. 521-532, October 2011.
[6] G. M. Rebeiz, K. Entesari, I. Reines, S. J. Park, M. A. El-Tanani, A. Grichener, A. R. Brown, "Tuning in to RF MEMS", *IEEE Microw. Mag.*, vol. 10, no. 6, pp. 55 – 72, June 2009.
[7] M. Daneshmand, R. R. Mansour, "RF MEMS Satellite Switch Matrices", *IEEE Microw Mag*, vol. 12, no. 5, pp. 92 – 109, May 2011.
[8] I. Jokić, M. Frantlović, Z. Đurić, M. Dukić, "RF MEMS/NEMS resonators for wireless communication systems and adsorption-desorption phase noise", *Facta Universitatis – Series Electronics and Energetics*, vol. 28, no. 3, pp. 345-381, 2015.
[9] A. Napieralski, C. Maj, M. Szermer, P. Zajac, W. Zabierowski, M. Napieralska, Ł. Starzak, M. Zubert, R.Kiełbik, P. Amrozik, Z. Ciota, R. Ritter, M. Kamiński, R. Kotas, P. Marciniak, B. Sakowicz, K. Grabowski, W. Sankowski, G. Jabłoński, D. Makowski, A. Mielczarek, M. Orlikowski, M. Jankowski, P. Perek, "Recent research in VLSI, MEMS and power devices with practical application to the ITER and DREAM projects", *Facta Universitatis – Series Electronics and Energetics*, vol. 27, no. 4, pp. 561-588, 2014.
[10] M. Lazic, M. Skender, S. Radosevic, "Generating driving signals for three phases inverter by digital timing functions", *Facta Universitatis – Series Electronics and Energetics*, vol. 13, no. 3, pp. 353-364, 2000.
[11] A. N. Al-Rabadi, "Carbon nano tube (CNT) multiplexers for multiple-valued computing", *Facta Universitatis – Series Electronics and Energetics*, vol. 20, no. 2, pp. 175-186, 2007.

[12] J. Vobecký "The current status of power semiconductors", *Facta Universitatis – Series Electronics and Energetics*, vol. 28, no. 2, pp. 193-203, 2015.

[13] M. Lamhamdi, P. Pons, U. Zaghloul, L. Boudou, F. Coccetti, J. Guastavino, Y. Segui, G. Papaioannou, R. Plana "Voltage and temperature effect on dielectric charging for RF MEMS capacitive switches reliability investigation" *Microel. Reliab.,* vol. 48 pp. 1248-1252, Sept. 2008.

[14] M. Matmat, K. Koukos, F. Coccetti, T. Idda, A. Marty, C. Escriba, J-Y. Fourniols, D. Esteve, "Life expectancy and characterization of capacitive RF MEMS switches", *Microelectron. Reliab.*, vol. 50, no. 9–11, pp. 1692-1696, 2010.

[15] L. Michalas, M. Koutsoureli, E. Papandreou, A. Gantis, G. Papaioannou "A MIM capacitor study of dielectric charging for RF MEMS capacitive switches", *Facta Universitatis – Series Electronics and Energetics*, vol. 28, no. 1, pp. 113-122, 2015.

[16] M. Koutsoureli, L. Michalas, G. Papaioannou, "Assessment of dielectric charging in micro-electro-mechanical system capacitive switches", *Facta Universitatis – Series Electronics and Energetics*, vol. 26, no. 3, pp. 239-245, 2013.

[17] Y. Lee, D. S. Filipovic, "Combined full-wave/ANN based modelling of MEMS switches for RF and microwave applications", In Proceedings of the IEEE Antennas and Propagation Society International Symposium, 2005, pp. 85-88.

[18] Y. Lee, Y. Park, F. Niu, B. Bachman, K. C. Gupta, D. Filipovic, "Artificial Neural Network Modelling of RF MEMS Resonators", *Int. J. RF Microw. C E, Special Issue: RF Applications of MEMS and Micromachining*, vol. 14, no. 4, pp. 302–316, July 2004.

[19] V. Litovski, M. Andrejevic, M. Zwolinski, "Behavioural modelling, simulation, test and diagnosis of MEMS using ANNs," In Proceedings of the *IEEE* International Symposium on Circuits and Systems ISCAS 2005, 2005, pp. 5182 - 5185.

[20] Y. Lee, D. S. Filipovic, "ANN based electromagnetic models for the design of RF MEMS switches", *IEEE Microw. Compon. Lett,*, vol. 15, no. 11, pp. 823-825, November 2005.

[21] Y. Lee, Y. Park, F. Niu, D. Filipovic, "Design and Optimization of RF ICs with Embedded Linear Macromodels of Multiport MEMS Devices," *Int. J. RF Microw C E,* vol. 17, no. 2, pp. 196-209, March 2007.

[22] G. H. Yang, Q. Wu, J. H. Fu, K. Tang, J. X. He, "An efficient modelling technique for RF MEMS phase shifter based on RBF neural network," In Proceedings of the International Conference on Microwave and Millimeter Wave Technology ICMMT 2008, 2008, pp. 475-478.

[23] Y. Mafinejad, A. Z. Kouzani, K. Mafinezhad, "Determining RF MEMS switch parameter by neural networks", In Proceedings of the IEEE Region 10 Conference TENCON 2009, 2009, pp. 1-5.

[24] Y. Gong, F. Zhao, H. Xin, J. Lin, Q. Bai, "Simulation and Optimal Design for RF MEMS Cantilevered Beam Switch", In Proceedings of the International Conference on Future Computer and Communication FCC '09, 2009, pp. 84-87.

[25] S. Suganthi, K. Murugesan, S. Raghavan, "Neural Network based realization and circuit analysis of lateral RF MEMS series switch," In Proceedings of the International Conference on Computer, Communication and Electrical Technology ICCCET 2011, 2011, pp. 260 - 265.

[26] Q. J. Zhang, K. C. Gupta, *Neural Networks for RF and Microwave Design*, Artech House, 2000.

[27] C. Christodoulou, M. Gerogiopoulos, *Applications of Neural Networks in Electromagnetics*, Artech House, 2000.

[28] P. Burrascano, S. Fiori and M. Mongiardo, "A rewiew of artificial neural network applications in microwave computer-aided design", *Int J RF Microw C E*, vol. 9, no. 3, pp. 158-174, 1999.

[29] Z. Marinković, V. Marković, "Temperature dependent models of low-noise microwave transistors based on neural networks", *Int. J. RF Microw. C E*, vol. 15, no. 6, pp. 567-577, 2005.

[30] Z. Marinković, G. Crupi, A. Caddemi, and V. Marković, "Comparison between analytical and neural approaches for multibias small signal modelling of microwave scaled FETs", *Microw. Opt.Techn. Lett.*, vol. 52, no. 10, pp. 2238-2244, 2010.

[31] J. E. Rayas-Sanchez, "EM-based optimization of microwave circuits using artificial neural networks: The state-of-the-art", *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 420–435, 2004.

[32] H. Kabir, Y. Cao, and Q. Zhang, "Advances of neural network modelling methods for RF/microwave applications," *Applied Computational Electromagnetics Society Journal*, vol. 25, no. 5, pp. 423-432, 2010.

[33] Z. Marinković, G. Crupi, D. Schreurs, A. Caddemi, V. Marković, "Microwave FinFET modelling based on artificial neural networks including lossy silicon substrate", *Microel. Eng.*, vol. 88, no. 10, pp. 3158-3163, 2012.

[34] M. Agatonović, Z. Marinković, V. Marković, "Application of ANNs in evaluation of microwave pyramidal absorber performance", *Applied Computational Electromagnetics Society Journal*, vol. 27, no. 4, pp. 326-333, 2012.

[35] Z. Marinković, O. Pronić-Rančić, V. Marković, "Small-signal and noise modelling of class of HEMTs using knowledge-based artificial neural networks", *Int. J. RF Microw. C E*, vol. 23, no. 1, pp. 34-39, 2013.

[36] Z. Marinković, N. Ivković, O. Pronić-Rančić, V. Marković, A. Caddemi, "Analysis and Validation of Neural Approach for Extraction of Small-Signal Models of Microwave Transistors", *Microelectron. Reliab.*, vol. 53, no. 3, pp. 414–419, March 2013.

[37] S. Di Nardo, P. Farinelli, F. Giacomozzi, G. Mannocchi, R. Marcelli , B. Margesin, P. Mezzanotte, V. Mulloni, P. Russer, R. Sorrentino, F. Vitulli, L. Vietzorreck, "Broadband RF-MEMS based SPDT", In Proceedings of the European Microwave Conference, 2006.

[38] Z. Marinković, T. Kim, V. Marković, M. Milijić, O. Pronić-Rančić, L. Vietzorreck, "RF MEMS Modelling with Artificial Neural Networks", In Proceedings of the MEMSWAVE 2013, 2013.

[39] Z. Marinković, T. Kim, V. Marković, M. Milijić, O. Pronić-Rančić, L. Vietzorreck, "Artificial Neural Network based Design of RF MEMS Capacitive Shunt Switches", submitted to *ACES - Applied Computational Electromagnetics Society Journal*

[40] Advanced Design System 2009, Agilent Technologies

[41] COMSOL Multiphysics 4.3, COMSOL, Inc.

[42] Zlatica Marinković, Ana Aleksić, Tomislav Ćirić, Olivera Pronić-Rančić, Vera Marković, Tomislav Ćirić, "Analysis of RF MEMS capacitive switches by using neural model of actuation voltage", 2nd International Conference on Electrical, Electronic and Computing Engineering (IcETRAN 2015), Silver Lake, Serbia, June 8-11, 2015, pp. MTI2.3.1-5.

[43] T. Ćirić, Z. Marinković, T. Kim, L. Vietzorreck, O. Pronić-Rančić, M. Milijić, V. Marković, "ANN Approach for Mechanical Characteristics Modelling of RF MEMS Capacitive Switches," submitted to *Journal of Electrical Engineering-Elektrotechnicky Casopis*

[44] Z. Marinković, T. Ćirić, V. Đorđević, O. Pronić-Rančić, T. Kim, M. Milijić, V. Marković, L. Vietzorreck, "ANN Approach for the Analysis of the Resonant Frequency Behavior of RF MEMS Capacitive Switches", In Proceedings of the First International Conference on Electrical, Electronic and Computing Engineering IcETRAN 2014, 2014, pp. MTI2.1.1-5

[45] T. Ćirić, Z. Marinković, O. Pronić-Rančić, V. Marković, L. Vietzorreck , "ANN Approach for Analysis of Actuation Voltage Behavior of RF MEMS Capacitive Switches", In Proceedings of the 12th International Conference on Advanced Technologies, Systems and Services in Telecommunications TELSIKS 2015, 2015.

[46] Z. Marinković, T. Ćirić, T. Kim, L. Vietzorreck, O. Pronić-Rančić, M. Milijić, V. Marković, "ANN Based Inverse Modelling of RF MEMS Capacitive Switches", In Proceedings of the 11th Conference on Telecommunications in Modern Satellite, Cable and Broadcasting Services TELSIKS 2013, 2013, pp. 366-369.

[47] L. Vietzorreck, M. Milijić, Z. Marinković, T. Kim, V. Marković, O. Pronić-Rančić, "Artificial neural networks for efficient RF MEMS modelling", In Proceedings of the XXXI URSI General Assembly and Scientific Symposium URSI GASS, 2014, pp. 1-3.

[48] T. Ćirić, Z. Marinković, T. Kim, L. Vietzorreck, O. Pronić-Rančić, M. Milijić, V. Marković, "ANN based inverse electro-mechanical modelling of RF MEMS capacitive switches", In Proceedings of the XLIX Scientific Conference on Information, Communication and Energy Systems and Technologies ICEST 2014, 2014, pp. 127-130.

[49] Z. Marinković, A. Aleksić, O. Pronić-Rančić, V. Marković, L. Vietzorreck, "Analysis of RF MEMS Capacitive Switches by using Switch EM ANN Models", accepted for *TELFOR journal*, in press

[50] Z. Marinković, A. Aleksić, T. Ćirić, O. Pronić-Rančić, V. Marković, L. Vietzorreck, "Inverse electro-mechanical ANN model of RF MEMS capacitive switches - applicability evaluation", In Proceedings of the XLX Scientific Conference on Information, Communication and Energy Systems and Technologies ICEST 2015, 2015.

[51] Z. Marinković, A. Aleksić, T. Ćirić, O. Pronić-Rančić, V. Marković, T. Ćirić, "Analysis of RF MEMS capacitive switches by using neural model of actuation voltage", In Proceedings of the 2nd International Conference on Electrical, Electronic and Computing Engineering IcETRAN 2015, 2015, pp. MTI2.3.1-5.