Efficient Modelling of an RF MEMS Capacitive Shunt Switch with Artificial Neural Networks

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Abstract—In this paper an efficient way of modelling an RF MEMS switch will be demonstrated. On the base of several full-wave numerical simulations of a switch, artificial neural networks (ANNs) are established to relate different input and output parameters of a switch. The good coincidence between the simulated data and the model is shown at the example of a capacitive shunt switch in coplanar technology. S-parameters of the switch or the resonant frequency are computed with high accuracy for different geometrical parameters, with the same data also the inverse problem of determining the required geometry for a given resonance is solved.

I. INTRODUCTION

RF MEMS switches are small mechanically reconfigurable components [1], which combine electrical with mechanical properties. Usually they are integrated as switching elements in bigger circuits like switch matrices, phase shifters or reflect-arrays. A single MEMS switch can easily be modelled with all available commercial full-wave software tools. As it is a 3D structure, normally fully 3D discretising tools based on finite differences or finite elements are required, but due to the aspect ratio, where large lateral dimensions are combined with a small height, also 2,5D or planar 3D tools are applicable. Although all these methods provide necessary accuracy, they are generally limited to a single analysis for a specific structure, and their computational overhead (run time, memory) becomes extensive when for an optimization a number of simulations with different mesh properties is needed. However, with several switches implemented into a larger circuit, the full-wave modelling of the entire structure or the optimization of this circuit becomes more time-consuming or even impossible. Therefore proper models of switches to be used in a circuit simulator are needed. These can be just S-parameters obtained by measurement or modelling or an equivalent circuit model, where the equivalent circuit elements are determined by the physical behaviour of the switch (see Fig. 1). If a scalable equivalent circuit model is used, the switch behaviour can be optimized for a certain system application. However, what is usually missing is a direct relation between the geometry of the switch and its behaviour.

Fig. 1: Sketch of the coplanar capacitive shunt switch [6] and simplified equivalent circuit

This can be established by using an ANN model for the switch. ANN based algorithms have a great advantage in reducing the computational cost, especially when implemented within a circuit simulator that has integrated tuning and optimization options. Based on the massively parallel nature of a neural network, which is capable of modelling nonlinear mappings of multiple input/output variables, this approach has provided an accurate device characterization and efficient prediction of unknown input-output relationships with low computational overhead. Thus, it allows fast calculation of output values for a set of arbitrary input parameters. For the application of RF MEMS devices first simple approaches have been published to describe the S-parameters of a shunt switch, dependent on the length and width or gap of the bridge [2,3], using switch membranes with simple rectangular geometries. However, most of the publications in that area deal with the modelling of the mechanical behaviour of single membranes [4,5].
In this contribution we analyse a coplanar capacitive shunt switch fabricated by FBK in Trento in a technology described in [6] (see Fig. 1). This shunt switch has a structured membrane with a solid centre part and a fingered part close to the anchors for adjusting electrical and mechanical parameters. The thin fingered part will reduce the stiffness and actuation voltage and influence the inductance, whereas the size of the solid part determines the size of the actuation pad underneath and thus the required pull-in voltage. Inductance and capacitance of the switch form a series resonator in the equivalent circuit such that the switch produces a short at the resonant frequency. Due to the frequency band of the application area the resonance has to be adjusted by changing the lateral dimensions of the membrane while keeping the mechanical properties.

As described in the next section, we develop suitable ANN models on the base of a set of full-wave numerical simulations obtained with ADS Momentum. As a result we will have a model, where the length of the solid \((L_s)\) and the length of fingered part \((L_f)\) are directly related to the scattering parameters over frequency. This will give the possibility to have results of a varied geometry within seconds. With the same data set we can also directly determine the position of the resonance frequency, and, as the third option, we can solve the inverse problem. By giving the desired resonance frequency and the length of the solid part fixed, we can directly obtain the required length of the fingered part.

With a limited number of numerical simulations we now can provide a set of models, where all the required properties can be computed within the given parameter range with high accuracy without employing time-consuming full-wave tools. The design and optimization process will be accelerated heavily by this procedure. A further goal of this approach is even to relate results obtained by electrical and mechanical modelling in the same model.

II. ARTIFICIAL NEURAL NETWORKS

Among the most frequently used structures of the artificial neural networks is the multilayer perceptron (MLP) artificial neural network (ANN) shown in Fig. 2 [7]. An MLP ANN consists of an input layer (layer 0), an output layer (layer \(N_i\)) as well as several hidden layers. Each connection between neurons is weighted. Neurons have assigned transfer functions, which are usually linear for input and output layer and sigmoid for hidden layers. Input vectors are presented to the input layer and fed through the network that then yields the output vector.

An ANN learns relationship among sets of input-output data (training sets) that are characteristics of the component under consideration by adjusting its parameters, i.e. connection weights and thresholds of the neuron activation functions. For this purpose, several algorithms have been developed. One of the basic training algorithms is backpropagation algorithm, which can be briefly described as follows. First the input vectors are presented to the input neurons and output vectors are computed. These output vectors are then compared with desired values and errors are computed. Error derivatives are then calculated and summed up for each weight and bias until whole training set has been presented to the network. These error derivatives are then used to update the weights and biases for neurons in the model. The training process proceeds until errors are lower than the prescribed values or until the maximum number of epochs (epoch - the whole training set processing) is reached. There are also modifications of this algorithm which have higher convergence than the backpropagation algorithm, as quasi Newton or Levenberg-Marquardt algorithms [7].

The most important feature of ANNs is their generalization capability i.e. the capability to provide the 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.

Unlike complex time-consuming electromagnetic models, once developed neural models give responses practically instantaneously because response providing is based on performing basic mathematical operations and calculating elementary mathematic functions (such as an exponential or hyperbolic tangent function). Neural networks have the capability of approximating any nonlinear function and the ability to learn from experimental data. Therefore, it is possible to develop neural model from source-response data points without the knowledge about the physical characteristics of the problem to be solved.

Despite ANN modelling requires sometimes the extensive time and effort to prepare the training datasets, the learning and generalization abilities and their speed qualified the ANNs as a competitive tool for smart modelling in different areas, and especially for modelling of RF and microwave devices [7]-[10].

III. NEURAL MODELLING OF RF MEMS SWITCH

A. S-parameter modelling

As mentioned in the introductory section, to avoid time consuming full-wave simulators, ANN can be used to predict the switch S-parameters for the given values of geometrical parameters, as shown in Fig. 3. As the figure shows, only
magnitudes of $S_{11}$ and $S_{21}$ (both expressed in dB) are modelled. To ensure the modelling accuracy, two separate ANNs are trained. Both ANNs have three input neurons corresponding to the switch geometry parameters $L_s$ and $L_f$, and the frequency. There is only one neuron in the output layer corresponding to the modelled parameter. As the numbers of hidden layers and hidden neurons cannot be a priori determined, several ANNs with different number of hidden neurons are trained for both structures, and the ones showing the best test statistics are chosen as the final model.

![Fig. 3. ANN model of RF MEMS switch S-parameters](image)

The data used for ANN model development and validation was obtained by full-wave simulation within ADS software package for the frequencies up to 40GHz. The $S$-parameters were simulated for 23 combinations of geometry parameters $L_s$ and $L_f$. 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. Then the ANNs aimed to model magnitudes of $S_{11}$ and $S_{21}$ were trained and tested. As mentioned earlier, for both networks structures with different number of hidden neurons were trained and compared. As all the ANNs learned the training data very accurate, the accuracy for the test values not used for training was the criteria to compare the ANNs. It was found that among the trained ANNs the best test statistics gave the following two-hidden-layer ANNs: for $S_{11}$ the ANN having 8 neurons in the first layer and 6 neurons in the second hidden layer and for $S_{21}$ the ANN with 8 neurons in both hidden layers. For illustration, Fig. 4 shows comparison of the ANN simulated scattering parameters (lines) and the corresponding reference values obtained by the full-wave simulations in ADS (symbols). The data refer to the combinations of geometrical parameter values that were not presented to the ANN during the ANN training procedure. It can be observed that there is very good coincidence between the simulated and reference values.

### B. Resonant frequency modelling

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 is proposed. 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. 5.

![Fig. 5. ANN model of RF MEMS switch](image)

Therefore, this ANN has two input neurons and one output neuron. The number of hidden neurons is determined during the ANN training, as mentioned above.

The ANNs aimed for the resonant frequency determination were trained and validated using the same simulated data as in the previous example. For that purpose, first for all 23 combinations of the geometrical parameters, the resonant frequency was determined from the simulated $S$-parameters. The training and test set correspond to the same 17 and 6 geometry parameter combinations as in the previous case.

<table>
<thead>
<tr>
<th>$L_s$ (μm)</th>
<th>$L_f$ (μm)</th>
<th>$f_{res-ANN}$ (GHz)</th>
<th>$f_{res-ADS}$ (GHz)</th>
<th>Rel. error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>250</td>
<td>25</td>
<td>13.7</td>
<td>13.689</td>
<td>0.08</td>
</tr>
<tr>
<td>250</td>
<td>75</td>
<td>12.4</td>
<td>12.403</td>
<td>0.02</td>
</tr>
<tr>
<td>350</td>
<td>25</td>
<td>11.6</td>
<td>11.550</td>
<td>0.43</td>
</tr>
<tr>
<td>350</td>
<td>75</td>
<td>10.7</td>
<td>10.638</td>
<td>0.58</td>
</tr>
<tr>
<td>450</td>
<td>25</td>
<td>10.2</td>
<td>10.127</td>
<td>0.71</td>
</tr>
<tr>
<td>450</td>
<td>75</td>
<td>9.5</td>
<td>9.499</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Among the trained ANNs, the best results were obtained by the ANN having only one hidden layer containing five neurons. 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%), confirming the accuracy of the ANN model.

C. Inverse modelling

As the design of RF MEMS switches requires not only analysis of the switch but also determining the switch geometry parameter values for achieving the desired criteria, as the very first results here ANNs are proposed to determine length of the fingers $L_f$ for fixed length of the solid part $L_s$ and a given resonant frequency. The ANN has, therefore, two input neurons corresponding to $L_s$ and $f_{res}$, and one output neuron corresponding to $L_f$, as shown in Fig. 6. The number of hidden layers is determined during the training. Once the network has been trained, the length of the fingers for any value of the solid part length and desired resonant frequency can be quickly calculated enabling in that way fast optimizations of the switch dimensions for satisfying the desired resonant frequency criteria.

![ANN model of RF MEMS switch](image)

Fig. 6. Inverse ANN model of RF MEMS switch

Using the same data used for developing the model of the resonant frequency dependence on the switch geometrical parameters, the ANNs for $L_f$ calculation were trained. It was found that the best results were achieved by the ANN which has two hidden layers containing 3 neurons each. As the illustration, Table II shows the ANN response for the different values of the $L_s$ and $f_{res}$ not seen by the ANN during the training. It should be noticed the ANN determined values differ from the expected ones by less then or around 5\%, which could be considered as quite good.

<table>
<thead>
<tr>
<th>$L_s$ (\textmu m)</th>
<th>$f_{res}$ (GHz)</th>
<th>$L_f$ (target) (\textmu m)</th>
<th>$L_f$ (ANN) (\textmu m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>250</td>
<td>13.7</td>
<td>25</td>
<td>24.5</td>
</tr>
<tr>
<td>250</td>
<td>12.4</td>
<td>75</td>
<td>76.5</td>
</tr>
<tr>
<td>350</td>
<td>11.6</td>
<td>25</td>
<td>19.5</td>
</tr>
<tr>
<td>350</td>
<td>10.7</td>
<td>75</td>
<td>70.7</td>
</tr>
<tr>
<td>450</td>
<td>10.2</td>
<td>25</td>
<td>21.4</td>
</tr>
<tr>
<td>450</td>
<td>9.5</td>
<td>75</td>
<td>76.6</td>
</tr>
</tbody>
</table>

TABLE II

RF MEMS SWITCH INVERSE MODELING RESULTS

IV. Conclusion

The trained ANNs give response practically in a moment, and therefore can be used for fast prediction of the scattering parameters and/or resonant frequency with the arbitrary grid of the considered geometrical parameters.

The further research will be directed to the developing of the inverse models by using the larger training data sets in order to decrease the prediction error. Also, in the future an analysis of the sensitivity of the switch output parameters on the geometrical parameters changes should be done in order to estimate the real accuracy of the ANN determined switch dimensions. A further activity is to extend the models to combine mechanical and electrical input and output parameters of the switch.

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