A Machine Learning-Based Microwave Device Model for Fully Printed VO₂ RF Switches

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Abstract — Fully printed vanadium dioxide (VO₂) based Radio Frequency (RF) switches have been recently developed for advanced frequency-reconfigurable RF electronics. A reliable and versatile model for the VO₂ switches is required for design and simulations in the modern Computer-Aided Design (CAD) tools. This paper proposes a machine learning (ML) based model for VO₂ RF switches, which is much more time and resource efficient as compared to the traditional device models. The computational efficiency, accuracy and robustness of the proposed model over a frequency range of 30 GHz is demonstrated through an excellent agreement between the modelled and measured results. The comparison between the measured and modelled results demonstrate a mean-square error (MSE) of lower than 5×10^{-4} and 5×10^{-3} for the magnitude and phase values over the complete frequency range.

Keywords — VO₂ switch, neural network, modelling, MLP, fully printed RF switch.

I. INTRODUCTION

Radio Frequency switches are one of the key drivers for the design of advanced frequency-reconfigurable circuits and systems. Conventionally, most RF switches, such as PIN diodes or Micro-electromechanical systems (MEMS) switches, are inherently cost-ineffective due to the involvement of the nanofabrication processes [1]–[2]. Recently, fully printed VO₂ switches have been developed, which have the potential to replace the conventional switches owing to its extremely low cost and unique soldering-free integration capability [3]. It is imperative to note that an accurate behavioral model for printed VO₂ switches is a primary requirement for design and simulations of frequency-reconfigurable circuits in modern microwave CAD tools. Traditionally, numerous approaches exist for developing CAD compatible device models. Though the existing approaches enable accurate development of the models, but the process is time consuming and resource (RAM, CPU) intensive. It is because the 3D simulators are based around either the finite element method (FEM) or finite difference method (FDM) [4], which ultimately leads to long design and optimization time. On the other hand, equivalent circuit models based on Simulation Program with Integrated Circuit Emphasis (SPICE) are usually fast with low computational requirements but it is challenging to develop the models for a multi-variable dynamic environment [5]. As an alternate to the traditional modeling techniques, researchers

are now looking at machine learning (ML) based models [6]–[8] and in this work, we focus on developing a behavioral model for printed VO₂ based RF switches.

Introduction of machine learning techniques in the domain of RF/microwave device modeling provides a stimulating platform to approximate the behavior of the devices without any explicit mathematical representations. Although machine learning is not a new technology, it is now rapidly gaining due to significant factors such as reasonable and powerful computational processing, continuously increasing the volume of vast datasets and reasonable data storage options. Machine learning (ML) technique is capable of handling multi-dimensional and multi-variety datasets in dynamic environments by enabling the model to learn and interpret without being explicitly programmed. Models, when exposed to new sets of data inputs, independently adapt and learn from earlier computations to interpret dataset and identify hidden insights. This involves the analysis of data and therefore enables us to set up automation of the analytical model using numerous ML algorithms. Moreover, features such as real-time and fast prediction ability makes them appealing for a device engineer to look beyond the conventional methods of modeling microwave devices. On the other hand, circuits and system designers can even pick up and place an accurate ML-based device model for analysis and simulation purposes. This in turn, can bring a paradigm shift in the domain of device modeling by integrating various device geometry and learning device behavior with more features to build an automation model using numerous ML algorithms. Subsequently, this will lead to an expedite design optimization process by avoiding numerous complex equations involved in conventional methods, with reduced computation time, accuracy, robustness and better prediction ability which ultimately leads to the enhancement in production yield.

Taking all the above features into account, the paper proposes the development of a printed VO₂ RF switch model using learning approach based around Artificial Neural Network (ANN). The proposed model implicitly models the RF behavior of the printed VO₂ switch for multiple inputs such as length, width, thickness and temperature for a wide frequency range of 0 to 30 GHz. The proposed approach can

quickly predict the behavior with very low computational overhead and can, therefore, handle extensive scale simulations for multi-input and multi-output variable datasets in a dynamic environment with high accuracy. The performance of the model is enumerated in terms of mean square error (MSE), correlation coefficient (R) and convergence time of the response variable.

II. VO₂ SWITCH FABRICATION AND CHARACTERIZATION

The fabricated VO₂ switch, as shown in Fig 1(a), uses Co-Planar Waveguide (CPW) transmission line (indicated by gray color). The VO₂ film (black color in the figure) has been printed on top of the CPW line. When the switch is at room temperature, the VO₂ film behaves as the dielectric, and the RF switch operates like a regular CPW transmission line and allows the RF signals to pass through (ON state). When the temperature goes up above the transition temperature (68 °C), the VO₂ film turns into metal and shorts the signal trace with the ground traces, resulting in an RF signal blockage (OFF state). A shunt switch configuration is shown in Fig 1(a).

The switch has been fully screen printed using VO₂ nanoparticle ink and silver nanoparticle ink. Sapphire substrate has been selected because of its low dielectric loss ($\epsilon_r = 9.3$, $\tan\delta = 0.0001$). By utilizing the screen printer (AUREL 900PA), initially, a single layer of silver has been printed for the CPW line with the thickness of the layer around 4 μm . Subsequently, decent conductivity of $1.8 \times 10^7 \text{ S/m}$ is achieved by drying the ink at 150 °C for 30 minutes in a convection oven. In the second step, VO₂ film has been printed on top of the CPW line using the same screen printer. Different thicknesses of the VO₂ switch has been achieved by printing the various number of layers. The printed VO₂ layers are dried using an Infrared radiation (IR) lamp, and eventually, the entire printed VO₂ switches are post-processed in a vacuum oven at 200 °C for 1 hour as the last step to further improve the performance.

All the printed VO₂ switches are measured using a pre-calibrated Vector Network Analyzer (VNA). The measurement setup is shown in Fig. 1(b) where VO₂ switches are located in the probe station with thermal chuck and connected to the VNA through the RF probes. The temperature is recorded from 20 °C to 100 °C with 10 °C increment to cover the switch's performance from ON state to OFF state with transition state. The frequency is from 10 MHz to 30 GHz with an 8 MHz step size.

Fig. 1. Printed VO₂ based RF switch(a) and the measurement setup(b).

III. DEVELOPMENT OF ANN BASED VO₂ RF SWITCH MODEL

A. Basic Preliminaries of ANN Based Model

In the human brain, neurons communicate with each other by sending signals through complex connections. ANNs are operated on the same principle and attempt to simulate the learning process of the brain using complex algorithms. Every connection is weight-directed which may have either positive or negative values attached to it. Fig. 2 represents a network structure with an arbitrary number of inputs being connected to neurons with associated weights on each connection. Subsequently, the weighted inputs are accumulated inside the processing unit. The desired value of the weighted sum is passed through the unit called activation function which acts as a linear or non-linear transfer function. Weighted sum always lies in the range $[0, \infty)$. However, if the weighted sum somehow accounts for zero, the bias is added to scale up the system response. The response y_j is evaluated using (1)

$$y_j = \psi \left(\sum_{i=1}^n w_{ji} x_i + \Theta_j \right) \quad (1)$$

where Θ_j is the bias, w_{ji} are synaptic weights and x_i corresponds to inputs provided to the system.

Fig. 2. Schematic representation of a single unit of neuron

Several single neuron units (known as perceptron) when combined, form a multi-layer perceptron (MLP). The proposed model, as shown in Fig. 3 is developed utilizing the basic MLP architecture of ANN which consists of an input layer, response layer and a couple of intermediate hidden layers with 25 neurons each. The fundamental reason for using two hidden layers for the proposed work is to provide more information so that it can easily learn patterns and features associated with the dataset of large volumes. Depending on the complexity of the network, neurons may vary.

Fig. 3. Proposed ANN-based model of Printed VO₂ RF Switch.

The weights are expressed in row matrices using (2)

$$w_{ki} = [w_{j1} \quad w_{j2} \quad w_{j3} \quad \dots \quad w_{jn}] \quad (2)$$

For feedforward MLP architecture, input to the node z in the hidden layer is expressed in (3)

$$n_z = \sum_{m=1}^q (x_m w_{mz}) + b_z; z = 1, 2, \dots, N \quad (3)$$

where w is the weight, b is the bias, N is the number of neurons in hidden layer and q is the number of neurons in the input layer. The output of the z^{th} neuron of the hidden layer is given by (4)

$$\text{output}_z = f(n_z) \quad (4)$$

where f is the activation function at each hidden layer. Activation functions are classified and defined as linear or non-linear transfer functions. For the proposed model, tan-sigmoid activation function, defined in (5), is used at each layer.

$$f(n_z) = \frac{2}{(1 + \exp(-2 * n_z)) - 1} \quad (5)$$

Inputs to the model are temperature varying from 20°C to 100°C, the dimension of the switch (length, width, and thickness). The frequency is swept from 0-30 GHz with a step size of 0.008 GHz. The measured two-port S-parameters recorded for each set of inputs are the response variables of the proposed model. The preprocessing unit of the model sets the magnitude of the response variables on the linear scale and phase variables into radian. It is imperative to note that scaling of the data minimizes the range of the variables which therefore in turn, will not only expedite the convergence of the model but improves the training efficiency and prediction ability of the model.

B. Training of the Proposed Model

The complete process of the development of the proposed model is shown through the flowchart in Fig. 4.

Fig. 4. Flowchart for the development of the proposed ANN-based switch model

The training of neural network involves optimization of weights and bias so that the fitness function (FF) is minimized. The FF, defined in terms of MSE, is expressed in (6). Dataset is segregated into a training set and test set, reserving 70% and 30% respectively.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_{meas} - y_{pred})^2 \quad (6)$$

where N is the number of samples, y_{meas} and y_{pred} are measured and predicted values of the response variables respectively. The model utilizes a modified Levenberg-Marquardt (LM) algorithm whose design is outlined as follows:

Step1: With the initial weights, randomly generated using the Nguyen-Widrow method [9], evaluate the total error. Unlike the random method of initializing weights and bias, Nguyen- Widrow method assists in expediting the training process and utilization of almost all neurons in input space.

Step2: Adjust and update weights and bias as shown in (7).

$$w_{k+1} = w_k - (J_k^T J_k + \mu I) J_k e_k \quad (7)$$

where w_k is the current weight, w_{k+1} is the next weight, e_k is the last total error, J_k is the current Jacobian matrix, μ is the combination coefficient, I represents the identity matrix and k is the index of iteration. Here, μI term is added to assist in fast convergence.

Step3: Evaluate the error using new weights.

Step4: Withdraw the step if the current total error is increased as a result of the update and increase μ by 10 times. Go to Step 2 and again update.

Step5: If the current total error is reduced after the update, then accept the step and decrease μ by 10 times.

Step6: Go back to step 2 with the new weights until the current total error is smaller than the required value or maximum iteration limit of 1000 is reached.

IV. MODEL VALIDATION

In the previous section, a complete framework has been developed for modeling the printed VO₂ based RF switch using ANN. This section evaluates the performance and discusses the validation and effectiveness of the proposed model. The performance of the model is also enumerated in terms of the correlation coefficient R defined in (8). The performance parameters are shown in Table I.

$$R = \sqrt{\frac{\left(N \sum_{i=1}^N y_{meas} y_{pred} - \sum_{i=1}^N y_{pred} \sum_{i=1}^N y_{meas} \right)^2}{\left(N \sum_{i=1}^N y_{pred}^2 - \left(\sum_{i=1}^N y_{pred} \right)^2 \right) \left(N \sum_{i=1}^N y_{meas}^2 - \left(\sum_{i=1}^N y_{meas} \right)^2 \right)}} \quad (8)$$

Table 1. Performance and Convergence Rate of the proposed model.

Response/ Performance	MSE (Train)	MSE (Test)	R(%) (Train)	R(%) (Test)	Converge Rate (secs)
$ S_{11} $	3.02e-4	4.33e-4	99.72	99.61	34
$\angle S_{11}$	7.34e-3	8.83e-3	99.20	99.01	41
$ S_{12} $	1.09e-4	3.12e-4	99.93	99.72	23
$\angle S_{12}$	3.28e-3	5.63e-3	99.91	99.87	55
$ S_{21} $	1.42e-4	2.83e-4	99.92	99.81	27
$\angle S_{21}$	3.58e-3	6.23e-3	99.87	99.81	83
$ S_{22} $	4.32e-4	6.76e-4	99.52	99.38	108
$\angle S_{22}$	6.14e-3	8.11e-3	99.12	99.11	112

It is quite apparent from Table I that the proposed model has been trained effectively with optimized sets of weights, bias and other tuning parameters. Moreover, the convergence rate of the model is very good pertaining to the fact that a high-volume dataset is used for training.

To prove the effectiveness, the proposed model is subjected to an unknown set of inputs. The performance of the model is observed for ON and OFF state of the switch with the same geometric attributes, utilizing 30% data reserved for test and validation purposes. An excellent agreement found between the measured S-parameters and the proposed model, shown in Fig. 5 and Fig. 6 validates the accuracy of the model. Relative to full-wave EM simulation where it takes typically around 5 minutes for complete execution, the proposed ANN-based model took only a few seconds to accomplish the process. With such high accuracy, the proposed RF switch behavioral model can be integrated into CAD tools for simulation of RF reconfigurable components such as filters or antenna.

Fig. 5. Comparison between measured S-parameters and the proposed model for Temp.=20°C, Width= 500μm, Thickness=34.4μm, Length=100μm.

V. CONCLUSION

In this paper, an ANN-based printed VO₂ RF switch behavioral model has been developed. The proposed model is novel and advanced possessing high prediction ability and good generalization capability. ANN-based approach very precisely models the RF switch performance which is evident from an excellent agreement between the measured S-parameters and the simulated model. The proposed modeling approach based on ML has a lot of potentials to bring a paradigm shift in modeling approach for printed and reconfigurable wireless system design and can be incorporated in the CAD tools for analysis.

Fig. 6. Comparison between measured S-parameters and the proposed model for Temp.=100°C, Width= 500μm, Thickness=34.4μm, Length=100μm.

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