CHAPTER 5

CHARACTERIZATION OF SINGLE AND DOUBLE BEAM SERIES LATERAL SWITCH

A study of a lateral switch with coplanar waveguide configuration has been reported in earlier work (Tang et al 2004), which shows an insertion loss of below 1 dB and an isolation of above 16 dB in the frequency range of 400 MHz to 20 GHz. In this work, the lateral RF MEMS series switch is focused for the following analysis.

- RF circuit design of single beam lateral MEMS series switch
- Static and dynamic characteristics of double beam RF MEMS lateral switch by calculating its characteristics parameters.
- Effect in losses due to variation of passive circuit component for single beam RF MEMS lateral switch
- Optimized mechanical design of capacitive micromachined RF MEMS switch

5.1 RF CIRCUIT DESIGN OF SINGLE BEAM LATERAL MEMS SERIES SWITCH

In general, MEMS switches can be classified into two main categories based on the directions of motion, namely vertical switch and lateral switch. The vertical switch performs out of wafer plane displacement and surface contact. The lateral switch performs in wafer plane displacement
and sidewall contact. Most of the reported MEMS switches are vertical motion switches; including the fixed - fixed beam switch (Goldsmith et al 1998), cantilever beam switch (Hyman 1999), toggle switch (Schauwecker et al 2002) and push - pull switch (Hah et al 2000). The main drawbacks of vertical switches are relatively complicated fabrication process and stiction problems during the release of the movable structures. Lateral motion switches have also been studied. In contrast to vertical switches, lateral switches have the benefit of co-fabrication. The actuator, contacts, conductor paths and the support structures can be fabricated in a single lithographic step. Besides, it is easy to get a mechanical force in opposing directions even when electrostatic designs are used.

In this work we propose an efficient approach based on neural network for analyzing the losses in ‘up’ and ‘down’ state of lateral RF MEMS series switch by calculating the S-parameters. The single beam structure has been analyzed in terms of its return and insertion losses with the variation of its passive circuit component values. The effect of design parameters has been analyzed and the lateral switch was realized with low insertion loss, high return loss, and high isolation. An efficient model for optimization of DMTL phase shift is derived efficiently using ANN. The results from the neural models trained by LM algorithm are in very good agreement with the theoretical results available in the literature.

5.1.1 RF Circuit Model of the Proposed Switch

A single beam lateral switch consists of a silicon core CPW and an electrostatic actuator, as shown in Figure 5.1 (a). A cantilever beam is fixed at one port. The free end of the cantilever beam comes into contact with the contact bump at the other port upon turning on the switch. The cantilever beam serves as the signal line alone. The ground lines beside the cantilever beam are extended toward the cantilever beam to avoid drastic increase in the
characteristic impedance. The width of the gap between the cantilever beam and the ground lines is 20 – 30 μm. At the free end of the cantilever beam, one ground line produces toward the cantilever beam further to serve as a fixed electrode. Therefore, no additional fixed electrode is required. When sufficient DC bias voltage is applied between the cantilever beam and the ground line, the cantilever beam is pulled toward the fixed electrode by electrostatic force until its free end hits the contact bump, resulting in the ‘up’ state of the switch. When DC bias voltage is removed, the mechanical stress of the beam overcomes the stiction forces and pulls the cantilever beam away, resulting in the ‘down’ state of the switch. Due to the asymmetrical layout of the two ports, the S-parameters obtained from the two ports are not reciprocal (Tang et al 2005). The return loss of port 2 is better than that of port 1 at the ‘down’ state since the open stub at port 2 is shorter than port 1. Hence, generally port 2 acts as the input port and port 1 acts as the output port to block more RF signal at the ‘down’ state of the switch. Figures 5.1 (b) and (c) show the cross sectional view and equivalent circuit of the lateral switch respectively. The model consists of a characteristic impedance $Z_0$ for the input and output sections of the silicon core CPW, a line resistor $R_1$ of the cantilever beam, a line inductor $L$ of the cantilever beam, a switch series capacitor $C_s$ (‘down’ state) or a contact resistor $R_c$ (‘up’ state), and a shunt coupling capacitor $C_g$. Except $Z_0$ other parameters are allowed to vary in order to fit the simulation results.

According to the T-equivalent circuit model, $S_{21}$ of the circuit can be given by

$$S_{21} = \frac{2}{2 + \left(\frac{Z_0 + Z_1 + Z_2}{Z_3} \right)} \frac{Z_0}{\left(\frac{Z_1 + Z_2 + Z_1Z_2/Z_3}{Z_0}\right)}$$

(5.1)

where

$$Z_1 = R_1 + j\omega L$$

(5.2)
\[
Z_2 = \begin{cases} 
\frac{1}{j\omega C_s} & \text{for ‘up’ state} \\
R_s & \text{for ‘down’ state} 
\end{cases} 
\] 

and

\[
Z_3 = 1/j\omega_g
\] 

At the ‘down’ state of the switch, the switch capacitance \( C_s \) is an important factor that affects the isolation of the switch. When \( S_{21} = 10 \, \text{dB} \) and

\[
\omega C_s Z_0 \left[ 2 - \omega^2 C_s L + \frac{C_s}{C_s} + \frac{R_s}{Z_0} \left( 1 + \frac{C_s}{C_s} \right) \right] \ll 1
\] 

the isolation of switch can be approximately expressed as

\[
S_{21} \approx j 2 \omega C_s Z_0
\] 

Therefore, the series capacitance \( C_s \) of the ‘down’ state switch can be extracted from the simulated isolation of the switch using Equation (5.5).

![Diagram](image.png)

Figure 5.1 (Continued)
At the ‘up’ state of the switch, the insertion loss and the return loss (Tang et al 2005) can be expressed as

\[
S_{21} = \frac{2}{2 + k_1 + jk_2} \quad \text{and} \quad S_{11} = \frac{k_1 + jk_2}{2 + k_1 + jk_2}
\]  
(5.7)

where

\[
k_1 = R_1 + R_c / Z_0 - \omega^2 C_g L \left(1 + \frac{R_c}{Z_0}\right)
\]

\[
k_2 = \omega \left[\left(R_1 + R_c + Z_0 + \frac{R_1 R_c}{Z_0}\right) + \frac{L}{Z_0}\right]
\]

\[
k_3 = \omega \left[\left(R_1 - R_c - Z_0 + \frac{R_1 R_c}{Z_0}\right) + \frac{L}{Z_0}\right]
\]

(5.8)

At low frequencies, when \(2 + k_1 \gg 0\) and \(k_2 \ll 2 + (R_1 + R_c) / Z_0\), the insertion loss and the return loss of the switch can be simplified as
The series inductance $L$ can be calculated by

$$L = \frac{Z_l \beta l}{\omega} = \frac{Z_l l \sqrt{\varepsilon_{\text{eff}}}}{c}$$

where $Z_l$ is the impedance of the cantilever beam, $l$ is the whole length of the cantilever beam, $\beta$ is the phase constant, $\varepsilon_{\text{eff}}$ is the relative effective permittivity, and $c$ is the speed of the light in vacuum.

5.1.2 ANN Model

The MLP neural model has been successfully used to analyze the S-parameters of ‘up’ and ‘down’ state of single beam lateral RF MEMS series switch with the frequency range up to 25 GHz. Adjusting the weights between the connections through learning is called training of neural network. Training is the process of optimizing the sum of squared differences error between the desired and actual values of output neurons.

The input ranges are $0.2 \Omega \leq R_1 + R_2 \leq 10 \Omega$, $10 \text{pH} \leq L \leq 200 \text{pH}$, $1 \text{GHz} \leq f \leq 25 \text{GHz}$ and $1 \text{fF} \leq C_s \leq 60 \text{fF}$ for calculating the S-parameters of the up and down state of the lateral RF MEMS series switch. By using these different data sets ($f$, $C_s$, $L$, $R_1+R_c$ and $C_g$) in the proposed neural network, we have calculated the value of the S-parameters. Differences between the target $S_{11}$ and $S_{21}$ using MATLAB and the actual outputs of the neural model $S_{11\text{ANN}}$ and $S_{21\text{ANN}}$ are calculated through the network to adopt its weights. The adaptation is carried out after presenting each dataset ($f$, $C_s$, $L$, $R_1+R_c$ and $C_g$) until the calculation accuracy of the network is deemed satisfactory to the intension.
5.1.3 Results and Discussion

The proposed ANN as shown in Figure 5.2 (a) was trained with four different training algorithms. After the comparison of root means square (RMS) error for four training algorithms, LM algorithm having least RMS error has been chosen for further training. Using all equation specified in the previous section, the S-parameters of both state of the proposed single beam lateral switch is calculated from initial value to 25 GHz range of frequency for the specification listed as in the input ranges of the neural network.

Figure 5.2 (b) shows the simulated isolation of ‘down’ state switch with various series capacitances of \( C_s \). The isolation of the ‘down’ state switch increases with the decrease in \( C_s \). The equivalent series capacitance \( C_s \) of our practical lateral switches is 3 - 10 fF. Up to 25 GHz, the isolation is higher than 25 dB for \( C_s = 3 \) fF and 15 dB for \( C_s = 10 \) fF.

Figure 5.2 (c) and (d) show the simulated results of the insertion loss and the return loss of the switch at the ‘up’ state with various \( R_1 + R_2 \). The RF performances of the switch at the ‘up’ state deteriorate with the increase in \( R_1 + R_c \). When \( R_1 + R_c \leq 2\Omega \), the insertion loss is less than 0.2 dB up to 10 GHz. When \( R_1 + R_c \) increases to 10 \( \Omega \), the insertion loss is larger than 0.8 dB at 10 GHz. The return loss decrease with increase in \( R_1 + R_c \). Therefore, the resistance sum \( R_1 + R_c \) should be made as small as possible to achieve low insertion loss and high return loss.
Figure 5.2 (a) Proposed ANN structure for single beam lateral switch analysis. Comparison of MATLAB and neural results (b) S-parameters with various capacitances $C_s$ at the ‘down’ state. (c) Insertion loss (d) Return Loss with various resistance sums at the ‘up’ state.

Figures 5.3 (a) and (b) show the simulated results (MATLAB (solid) and ANN (dashed) show that the RF performances of the switch at the ‘up’ state for various values of inductances. In all curves both results are having better coincident. The results become better when the inductance (L) increases from 10 to 100 pH. However, the insertion loss and the return loss begin to deteriorate when the inductance increases further, especially at a high
frequency range. From these figures we observed that there are very good agreement between the results of the neural model and the results computed by MATLAB for the S-parameter calculation of series lateral RF MEMS switch.

![Graph A](image1.png) ![Graph B](image2.png)

**Figure 5.3** Comparisons of MATLAB and neural network simulation results of S-parameters with different inductance values (a) Insertion loss (b) Return Loss

### 5.2 STATIC AND DYNAMIC CHARACTERISTICS OF DOUBLE BEAM RF MEMS LATERAL SWITCH

This work presents neural model implementation for mechanical modeling of RF MEMS lateral double beam switch. We propose an efficient approach based on ANN for analyzing the static and dynamic characteristics of RF MEMS lateral switch by calculating its characteristics parameters. ANN model is trained with five learning algorithms and the results from the neural model trained by LM back propagation algorithm are highly agreed with MATLAB calculated results. The neural network with LM algorithms shows better results with highest correlation coefficient (0.5844) along with lowest root mean square error (0.0539). The threshold voltage and frequency
response of a cantilever beam used in the double beam lateral switch which finds application in high frequency transmitting, receiving and signal routing has been analyzed using neural network.

Generation of training and testing datasets are realized from MATLAB simulation. The cantilever beam used in the switch has been analyzed in terms of its static threshold voltage, dynamic frequency response and effective mass. Due to the optimization of generalized dimension of actuation part, the datasets for the mechanical design of the switch are obtained. The resultant input and output relationship are mapped using the neural model. Based on valid range of input parameters, neural networks are trained and tested. Although extensive time and effort are required for preparing the dataset, once the network is trained, the proposed model accurately predicts the device responses for arbitrary inputs within the desired range.

5.2.1 Theory of Double Beam Lateral RF MEMS Switch

In this work, double beam RF lateral switch consisting of a silicon core finite ground coplanar waveguide (FGCPW) and an electrostatic actuator is designed as shown in Figure 5.4 (a) for ANN implementation since it provides low insertion loss and high power handling. FGCPW is formed by thick single crystal silicon plate that has been coated with thin layer of aluminum to make the RF signal propagation not only along the metal on the top surface, but also on the sidewalls of the transmission line. In this switch, two cantilever beams are employed and can be used as signal lines together to propagate RF signal (Tang et al 2005). Both the fixed connections of the two cantilever beams are from the same port and the two contact tips are on the other port. At the free end of the two cantilever beams, both ground lines extend towards the nearby cantilever beams to serve as their fixed electrodes respectively.
When sufficient DC bias voltage is applied between the cantilever beam and the ground line, the cantilever beam is pulled toward the fixed electrode by electrostatic force until its free end hits the contact tip, resulting in the upstate of the switch. When DC bias voltage is removed, the mechanical stress of the beam overcomes the stiction forces and pulls the cantilever beam away, resulting in the downstate of the switch. Figures 5.4 (b) & (c) respectively show the equivalent circuit model and top view of the electrostatic actuator used in the modeling.

![Figure 5.4](image)

**Figure 5.4** (a) Schematics top view (b) Equivalent circuit of double beam lateral switch (c) Top view of the electrostatic actuator
5.2.1.1 Mechanical modeling of proposed switch

When a micro machined circuit is designed, it is important to consider the switching voltage required for its operation. The low actuation voltage can be achieved through the optimization of the geometrical dimensions of the actuation part. In the top view of the electrostatic actuator used in the modelling, the actuator consists of four components: a suspended cantilever beam serving as a movable electrode, an anchor on the substrate to support the cantilever beam, a fixed electrode opposite to the cantilever beam and a contact tip. The cantilever beam OC is a beam-mass structure. For the beam part OA, the width is \( w_1 \) and the length is \( l_1 \). For the mass part AC, the width is \( w_2 \) and the length is \( l_2 + l_3 \) in which \( l_2 \) is the length of the electrode section AB and \( l_3 \) is the length of BC. The mass width \( w_2 \) is designed to be relatively wider than the beam width \( w_1 \) so that low threshold voltage can be maintained and greater deformation of the electrode section may be avoided.

5.2.1.2 Static threshold voltage by mechanical model

Assuming the electrode part of the cantilever beam is subjected to a uniform load, the equivalent stiffness \( k \) of the cantilever beam can be derived by the expression (Liu et al 2010)

\[
k = \frac{12E_1E_2I_1I_2}{\left(\frac{3}{2}l_2^3 + 2l_2l_3^2\right)E_1I_1 + \left(4l_1^3 + 9l_2l_1^2 + 6l_2^2l_1 + 6l_2^2l_3 + 6l_2l_3l_2\right)E_2I_2}
\]  

(5.11)

\( E_1 \) and \( E_2 \) are the Young’s moduli of the narrow and wide part of the beam respectively (Gere & Timoshenko 1997). \( I_1 \) and \( I_2 \) are the moments of inertia of the cross sectional area of the narrow and wide part of the beam respectively. We assume that \( E_1 = E_2 = E_{si} = 140 \text{ GPa} \)}
where $E_{si}$ is the Young’s modulus of the single crystal silicon (140 GPa) and $t$ is the height of the cantilever beam. After the deposition of aluminum on the top surface of the beam, it becomes the beam which is made of single crystal silicon partially covered with aluminum. Therefore and $E_1, E_2, I_1$ and $I_2$ can be given by

$$E_1 = \frac{E_{si}w_1 + 2E_{al}w_{al}}{w_1 + 2w_{al}}$$ (5.14)

$$I_1 = \frac{1}{12}(w_1 + 2w_{al})^3 t$$ (5.15)

$$E_2 = \frac{E_{si}w_1 + 2E_{al}w_{al}}{w_2 + 2w_{al}}$$ (5.16)

$$I_2 = \frac{1}{12}(w_2 + 2w_{al})^3 t$$ (5.17)

where $E_{Al}$ is the Young’s modulus of aluminum coated portion of beam (70 GPa), $w_{Al}$ the thickness of aluminum deposited at sidewalls of the silicon beam. Distance between the ends of two electrodes $g$ and the threshold voltage $V$ an be related by solving the equation $F_e(g) = F_r(g)$ where

$$F_e(g) = \frac{E_{al}I_2tV^2}{2g^2}$$ (5.18)

$$F_r(g) = k(g_0 - g)$$ (5.19)
are the electrostatic and restoring forces respectively with $\varepsilon_0$ is the permittivity of the air ($8.845 \times 10^{-12}$ F/m).

### 5.2.1.3 Dynamic frequency response

The frequency response of the cantilever beam is useful to determine the switching time and the mechanical bandwidth of the lateral switch (Liu et al 2010). Using Laplace transform, the frequency response of the cantilever beam with small vibration amplitude can be obtained as

$$\frac{Y(j\omega)}{F(j\omega)} = \frac{1/k}{1-(\omega/\omega_0)^2 + j\omega/(Q\omega_0)}$$

(5.20)

where $Y$ is the lateral displacement of the cantilever beam relative to the origin of the fixed electrode, $F$ is the electrostatic force, $\omega$ is the working angular frequency, $k$ is the effective stiffness, $\omega_0$ is the natural resonant angular frequency and $Q$ is the quality factor of the cantilever beam. $\omega_0$ and $Q$ are expressed as

$$\omega_0 = \sqrt{k/m} \quad \text{and}$$

(5.21)

$$Q = k/((\omega_0 b) \text{ respectively}.$$

(5.22)

where $m$ and $b$ are the effective mass and damping coefficient of the simplified system. The quality factor $Q$ of the cantilever beam is determined by several variables such as the pressure, the temperature and the intrinsic material dissipation. The quality factor is also an important component for the switching time calculation.
5.2.1.4 Dynamic effective mass

It is noted that the effective mass of the cantilever beam is not equal to the actual mass of the cantilever beam since only the end portion of the cantilever beam is moving. Assume the cantilever beam is subject to a concentrated load $P$ at the center of the electrode section of the cantilever beam. Based on Figure 5.4 (c), we can consider the displacement $y_k$ and kinetic energy $E_k$ of the cantilever beam at three portions, respectively.

The first part is the length of the beam ranging from $0 \leq x \leq l_1$. Its kinetic energy $E_{kl}$ is given by (Liu et al 2010)

$$E_{kl} = \frac{1}{2} m_i \left( \frac{P}{2E_i I_1} \right)^2 \left( \frac{-4l_1^4 + 25l_1^3 l_2 + 10l_1^2 l_2^2}{30} \right)$$  \hspace{1cm} (5.23)

Where $m_i = \left( \rho_s w_1 + 2 \rho_m w_m \right) l_1 t$  \hspace{1cm} (5.24)

The second part is from the beginning of the electrode to the center of the electrode of the cantilever beam ($l_1 \leq x \leq \left( l_1 + l_2/2 \right)$). The kinetic energy $E_{k2}$ is given by (Liu et al 2010)

$$E_{k2} = \frac{1}{2} m_2 \left[ \frac{P}{E_i I_1} \right]^2 \left( \frac{l_1^2 (l_1 + l_2)^2}{8} + \frac{P^2}{E_i I_1 E_2 I_2} \frac{l_1 l_2^2 (l_1 + l_2)}{24} + \left( \frac{P}{E_2 I_2} \right)^2 \frac{49l_2^4}{5760} \right]$$  \hspace{1cm} (5.25)

where $m_2 = \left( \rho_s w_2 + 2 \rho_m w_m \right) l_2 t$  \hspace{1cm} (5.26)

The third part is from the center of the electrode to the end of the cantilever beam and is given as ($l_1 + l_2/2 < x \leq l_1 + l_2 + l_3$). The kinetic energy $E_{k3}$ is given by
\[ E_{k3} = \frac{1}{2} m_2 \left( \frac{P(l_1^2 + l_1 l_2)}{2E_1 I_1} + \frac{P l_2^2}{8E_2 I_2} \right)^2 \left( \frac{1}{2} + \frac{l_3}{l_2} \right) \]  

(5.27)

Therefore, the total kinetic energy \( E_k \) is given by

\[ E_k = E_{k1} + E_{k2} + E_{k3} = \frac{1}{2} m y_m^2 \]  

(5.28)

where the velocity \( y_m \) at the end of the cantilever beam is

\[ y_m = \frac{P(l_1^2 + l_1 l_2)}{2E_1 I_1} + \frac{P l_2^2}{8E_2 I_2} \]  

(5.29)

5.2.2 Proposed ANN Model

Two back propagation feed forward ANN architectures (ANN-S for static threshold voltage and ANN-D for dynamic frequency response and mass analysis) are proposed for analysis in this work and are shown respectively in Figures 5.5 (a) and (b). All model parameters are allowed to vary and MATLAB simulation is used to generate the datasets for ANN models. The circuit parameters and dimension of actuated part are selected as input and threshold voltage is the output for ANN-S while length ratio, \( w_2 \), \( Q \) and frequency of operation are input and frequency response and effective mass are outputs for ANN-D.

The selected ranges of input parameters are as follows: \( 0.1 \leq (l_1/(l_1+l_2)) \leq 0.95 \), \( 4 \mu m \leq g_0 \leq 10 \mu m \), \( 2 \mu m \leq w_1 \leq 5 \mu m \) and \( 2.5 \mu m \leq w_2 \leq 20 \mu m \) for ANN-S and \( 0.1 \leq Q \leq 3 \), \( 0.1 \) KHz \( \leq f \leq 100 \) KHz and \( 440 \mu m \leq (l_1+l_2) \leq 540 \mu m \) for ANN-D respectively. The ratio of training to test data records employed in the experiment is 60:40. This means that with 468 data records, there are 280 records for the training set and 187 records for
the test set. The chosen best trained LM algorithm uses input vectors and corresponding target vectors to train the neural networks. The number of hidden units directly affects the performance of the network. Therefore, many experimental investigations are conducted. The number of hidden nodes determined to provide the optimal result are 10 for first and 6 for second hidden layers respectively. Thus the architecture of network obtained is 5x10x6x1 for ANN-S and 4x10x6x2 for ANN-D. The number of input nodes is 5 and 4 for ANN-S and ANN-D respectively, representing the geometrical parameters of the switch that affect outputs. The numbers of output nodes are 1 and 2 for ANN-S and ANN-D respectively.

Figure 5.5  Feed forward ANN architecture with input - output parameters for (a) Static (ANN-S) (b) Dynamic behaviour of double beam switch (ANN-D)

In order to evaluate the performance of the ANN models, the mean square error (MSE) and the correlation coefficient ($R^2$) as defined below are calculated in terms of the difference between the output of ANNs and training datasets:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i)^2$$  \hspace{1cm} (5.30)
where \( N \) is the total number of data sets, \( \hat{x}_i \) is input dataset, \( x_i \) is trained ANN output and \( \bar{x}_i \) is mean of \( x_i \).

### 5.2.3 Results and Discussion

Neural structures were trained with five different training algorithms. Figure 5.6 (a) shows the RMS error comparison of five training algorithms for the calculation of frequency response, effective mass and resonant frequency. When the performance of neural models is compared with each other, the best results were obtained from the models trained with LM algorithm. The LM method combines the best features of the Gauss-Newton technique and the steepest-descent method, but avoids many of their limitations. In particular, it generally does not suffer from the problem of slow convergence. To prove the efficiency and accuracy of the developed ANN models, the selected range of input values are used and the networks are validated. The comparison of calculated threshold voltage in terms of original gap between two electrodes, \( g_0 \) and the beam width \( w_1 \) from the neural networks and the simulated results are shown in Figures 5.6 (b) and (c) respectively.

Figure 5.6 (b) shows that the threshold voltage \( V_{th} \) decreases when the original gap between the two electrodes \( g_0 \) decreases or the length sum \( (l_1 + l_2) \) increases. When the cantilever beam length ratio \( l_2/(l_1 + l_2) \) is within the range of 30 – 75 %, \( V_{th} \) only changes within 10% of the minimum value of \( V_{th} \) which is referred to as \( V_{thmin} \). The corresponding length ratio \( [l_2/(l_1 + l_2)]_{min} \) to \( V_{thmin} \) is 50% when \( w_1 = 2.4 \ \mu m \), \( w_2 = 5 \ \mu m \) and \( w_{AL} = 0 \).
It also shows that $l_2/(l_1 + l_2)$ is almost independent of the initial gap $g_0$ and the length sum $(l_1 + l_2)$. Figure 5.6 (c) shows that the threshold voltage $V_{th}$ is more dependent on the beam width $w_1$ than the mass width $w_2$. The effect of the mass width $w_2$ is negligible. The threshold voltage $V_{th}$ increases with beam width $w_1$. In the Figure 5.6 (d), the variation in the frequency response amplitude of the cantilever beam is simulated with different quality factors.

Figure 5.6 (a) Bar chart comparisons of RMS error of training algorithms. Comparison of ANN and MATLAB results of $V_{th}$ (b) with various lengths ratio (c) with various cantilever beam widths (d) Variation in of cantilever beam with different quality factor
It shows that the frequency response amplitude at 15 KHz is increased when the quality factor ranges from 0.2 to 2.0. When $Q \leq 0.5$, it has a slow switching time; when $Q \geq 2$ it has a long settling time. In practice, it is beneficial for the switching time that the quality factor of the cantilever beam is designed by $0.5 \leq Q \leq 2$. The performance of neural network in achieving the results in target output of the threshold voltage has been analysed in terms of correlation coefficient and mean square errors for different length ratio and the results are given in Table 5.1.

**Table 5.1** Calculated mean square error and correlation coefficient of threshold voltage calculation for 440 µm and 500 µm length ratio with different initial gap

<table>
<thead>
<tr>
<th>$g_0$ (µm)</th>
<th>$l_1/(l_1 + l_2) = 440$µm</th>
<th>$l_1/(l_1 + l_2) = 500$µm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSE</td>
<td>$R^2$</td>
</tr>
<tr>
<td>4</td>
<td>0.0137</td>
<td>0.8099</td>
</tr>
<tr>
<td>6</td>
<td>0.0013</td>
<td>0.9999</td>
</tr>
<tr>
<td>8</td>
<td>0.0159</td>
<td>0.9569</td>
</tr>
<tr>
<td>10</td>
<td>0.0477</td>
<td>0.8899</td>
</tr>
</tbody>
</table>

Figure 5.7 show the comparison results of MATLAB (solid) and ANN (dashed) with values of both having better agreement. Figure 5.7 (a) shows the part mass $m_1, m_2$ and the effective mass $m$ of a cantilever beam changes with the ratio of $l_2/(l_1 + l_2)$ when $l_3 = 10$ µm and $l_1 + l_2 = 440$ µm. It shows that the effective mass $m$ is mainly determined by the mass of the electrode part $m_2$. The effective mass $m$ is 5 – 85 % of the actual total mass of the cantilever beam $[m_1 + m_2 (1 + l_3/l_2)]$ when the ratio of $l_2/(l_1 + l_2)$ is within the range of 30 – 75 %. Figure 5.7 (b) shows that the natural resonant frequency of the cantilever beam changes with the ratio of $l_2/(l_1 + l_2)$ and the sum of $(l_1 + l_2)$. It shows that the natural resonant frequency of the cantilever
beam changes slightly when $l_2/(l_1 + l_2)$ is within the range of 30 – 75 %. For example when $l_3 = 10 \, \mu m$ and $l_1 + l_2 = 440 \, \mu m$, the resonant frequency is $15 \pm 0.5 \, kHz$ as $l_2/(l_1 + l_2)$ is within the range of 0.3 - 0.75. The natural resonant frequency of the cantilever beam decreases with the increase of $l_1 + l_2$ due to the increase of the effective mass and the decrease of the stiffness of the cantilever beam.

Two parameters namely correlation coefficient and MSE values were used for the performance evaluation of the models and comparison of the results for prediction of S-parameters. The higher value of correlation coefficient and a smaller value MSE mean a better performance of the model. The values of these two parameters for the proposed neural network in calculating the resonant frequency and different masses has been given in Table 5.2. From Figures 5.6 and 5.7, it is observed that there is an excellent agreement between the ANN & theory result based on low MSE and higher correlation coefficient as in Table 5.2.

![Figure 5.6](image1.png)  
(a) 

![Figure 5.7](image2.png)  
(b) 

**Figure 5.7** Comparison of MATLAB and ANN results of (a) Effective mass ($m$) and part mass ($m_1, m_2$) of the cantilever beam versus the length ratio (b) Natural resonant frequency versus the length ratio
The above table shows that the neural network provides better results in terms of the higher correlation coefficient, which measures the strength and direction of the linear relation between two variables (actual and predicted values) of $R^2 = 0.8446$ (0.0284) with minimum mean square error of the model of 0.9184 (0.0139) for threshold voltage calculation in terms of various length ratio and beam widths.

Table 5.2  Calculated mean square error and correlation coefficient for mass and resonant frequency calculation

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Mass Calculation</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m (ng)</td>
<td>$m_1$ (ng)</td>
<td>$m_2$ (ng)</td>
</tr>
<tr>
<td>MSE</td>
<td>0.0624</td>
<td>0.1925</td>
<td>0.0921</td>
</tr>
<tr>
<td>Correlation coefficient</td>
<td>0.9375</td>
<td>0.7974</td>
<td>0.8446</td>
</tr>
<tr>
<td>Parameters</td>
<td>Resonant frequency calculation</td>
<td>(l_1 + l_2) (µm)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>440 (µm)</td>
<td>500 (µm)</td>
<td>540 (µm)</td>
</tr>
<tr>
<td>MSE</td>
<td>0.0914</td>
<td>0.1956</td>
<td>0.2192</td>
</tr>
<tr>
<td>Correlation coefficient</td>
<td>0.8057</td>
<td>0.7844</td>
<td>0.7790</td>
</tr>
</tbody>
</table>

5.3  EFFECT IN LOSSES DUE TO VARIATION OF PASSIVE CIRCUIT COMPONENT FOR SINGLE BEAM RF MEMS LATERAL SWITCH

In this work, single beam ‘up’ and ‘down’ state loss analysis is carried out using neural networks. Generation of training and testing datasets are realized from MATLAB simulation. Due to the optimization of generalized dimension of actuation part, the S-parameters of ‘up’ and ‘down’ state of RF lateral switch and low actuation voltage are obtained. The resultant input and output relationship are mapped using the neural model. Based on valid range of input parameters, neural network are trained and
tested. The neural networks show better results with the highest correlation coefficient (difference between the actual and neural predicted values) (0.9998) and lowest root mean square error (0.0039).

5.3.1 RF Modeling of the Lateral SPDT Switch

The equivalent circuit for the double - beam switch as shown in Figure 5.4 (b) can be framed from circuit model of the single beam switch by considering the resistor and inductance as twice \( R_1 = R_{10}/2, R_c = R_{c0}/2 \), \( L = L_{0}/2 \), and the capacitance value as half that of single beam model \( (C_s = 2C_{s0}, C_g = 2C_{g0}) \) with the assumption that the two cantilever beams are identical (Liu et al 2010). Hence, only the circuit model of the single beam switch is discussed in this section as shown in Figure 5.1 (c), which could also be used for the double-beam switch model. \( C_g \) is the coupling capacitance between the cantilever beam and the fixed electrode, which protuberates toward the cantilever beam from the ground line. It can be estimated using

\[
C_g = \varepsilon_0 l_2 t + C_f
\]

where \( l_2 \) is the length of the electrode part of the cantilever beam, \( t \) is the thickness of the beam, \( g \) is the distance of the gap between two electrodes and \( C_f \) is the fringing field capacitance.

5.3.2 Proposed ANN Model

A back propagation feed forward ANN are utilized in this work and is shown in Figure 5.8 (a). All model parameters are allowed to vary and MATLAB simulation is used to generate the datasets for ANN models. The circuit parameters of RF model are selected as input and insertion and return loss are the outputs. The selected ranges of input parameters are given as follows: \( 1 \Omega \leq (R_1+R_2) \leq 10 \Omega \), \( 20 \text{ fF} \leq C_g \leq 125 \text{ fF} \), \( 10 \text{ pH} \leq l \leq 300 \text{ pH} \).
1 GHz $\leq f \leq$ 26 GHz. The ratio of training to test data records employed is 70:30. This means that with 384 data records, there are 269 records for the training set and 115 records for the test set. The LM algorithm uses input vectors and corresponding target vectors to train the neural networks. The number of hidden units directly affects the performance of the network. Therefore, many trials are conducted and the number of hidden nodes determined to provide the optimal result are 8 for first and second hidden layers. Finally, the architecture of network is 5x8x8x2. The number of input nodes is 5, the number of the hidden nodes is set to 8 and the number of output nodes is 2 respectively.

5.3.3 Results and Discussion

The proposed neural structures are trained with five different training algorithms using LM algorithm. Figure 5.8 (b) shows the RMS error comparison of five training algorithms for the calculation of S-parameters. When the performance of neural models is compared with each other, the best results were obtained from the models trained with LM algorithm.

(a) Feed forward ANN architecture of single beam lateral switch analysis with input-output parameters (b) Bar chart comparisons of RMS error of training algorithms
Two parameters namely correlation coefficient and MSE values were used for the performance evaluation of the models and comparison of the results for prediction of S-parameters. The higher value of correlation coefficient and a smaller value MSE mean a better performance of the model.

To prove the efficiency and accuracy of the developed ANN models, the selected range of input values are used and the networks are validated. The comparison of predicted S-parameters (Isolation, return and insertion loss) from the networks and the simulated results are shown in Figure 5.9 (a) for ‘down’ state, and Figures 5.9 (b) and (c) for ‘up’ state return an insertion loss respectively. Figure 5.9 (a) shows that in the ‘down’ state the isolation of the switch increases with the decrease in $C_s$. Figures 5.9 (b) and (c) indicate that the RF performances of the switch in terms of return and insertion loss of the ‘up’ state. It is clear that the performances are improved when $C_g$ increases from 10 to 60 fF. The dip at 1.2 GHz for $C_g = 60$ fF indicates the maximum level of improved performances in return loss. After that the return loss performance of the closed switch begins to deteriorate when $C_g$ is increasing further to 125 fF.

Figure 5.9 (Continued)
When $C_g$ is 60 fF, the insertion loss and the return loss of the switch get to their optimal value since a resonance occurs at the operating frequency range and the losses only depend on the total resistance of the circuit. Therefore, for the design of RF lateral switch having high performance with low insertion and high isolation, the design parameters should be carefully chosen and optimized. The neural network provides better results in terms of the higher correlation coefficient. The correlation coefficient of 0.9999 (0.9998) and minimum mean square error of 0.0013 (0.0027) for threshold voltage calculation in varying length ratio (beam width) has been achieved for proposed neural model.

5.4 **OPTIMIZED MECHANICAL DESIGN OF CAPACITIVE MICROMACHINED RF MEMS SWITCH**

In this work, the neural modeling of optimized design for pull-in instability reduction of micromachined capacitive shunt RF MEMS switch is
concentrated. Prediction of effective dielectric constant and hence the critical collapse voltage that represents the bridge position instability for two typical bridge geometrics have been derived using neural network. The effects of residual stress, length of center conductor and the gap between the bridge and center conductor of switch in lowering the driving voltage have been studied.

Based on the neural model results, we have observed the reduction of 3 V in critical collapse voltage for an increase of 10 µm in length of center conductor. We have also noted the strong variation in critical collapse voltage (reduction of 0.8 V for 1 MPa residual stress reduction) with respect to residual stress change. We achieved the reduction of 1.5 V in collapse voltage by reducing the gap between the bridge and the center conductor by 0.1 µm. Among the two structures considered, the structure with lower width of the center conductor proved as optimum structure in achieving low critical collapse voltage. Further, the performance of trained neural network with the training datasets derived from MATLAB simulation has been evaluated in terms of convergence speed and mean square error.

5.4.1 Introduction

There are four kinds of MEMS based devices that would find application in RF system: capacitive micro machined switches, tunable capacitors, inductors and filters. Although most of these devices are still in the developing stage, capacitive micro machined switches could enter the commercial market soon. Wireless applications such as the transmit/receive switches in the cellular telephones are now a days replaced by capacitive micro machined switches (Muldavin & Rebeiz 2001c). It could also be used in time delay circuits such as phased array radars and communications antennas. These switches consume power only during actuation in terms of microwatts, whereas the existing switches in the cellular telephones consume milliwatts of power continuously thereby draining the batteries. Also, the
shunt capacitive micro machined switches allow for a large ‘down’ state and ‘up’ state capacitance ratio \( C_d/C_u \) of 20/100 which is necessary for wireless communications. These switches have the versatility to be fabricated on almost any silicon substrate. Some of the disadvantages of MEMS switches include: slow switching speed (2 - 10 µs), high actuation voltage (15 - 80 V) and hot switching in high power applications (>2 W) (Muldavin & Rebeiz 2000a).

5.4.2 Theory of Micromachined Capacitive Shunt RF MEMS Switch

The micromachined capacitive shunt MEMS switch contains a thin metal membrane called bridge which is suspended over a dielectric film deposited on top of the conductor and fixed at both end of two ground conductor of coplanar waveguide line as shown in Figure 5.10 (a). When an electrostatic potential is applied between the bridge and center conductor, the attractive electrostatic force pulls the bridge down towards the dielectric layer (Huang et al 2001). The dielectric layer serves to prevent stiction between the bridge and center conductor, as well as to provide a low impedance path between two contacts.

5.4.2.1 Pull-in instability of bridge

Figure 5.10 (b) shows the simplified model of bridge as fixed-fixed beam. Here \( X \) - and \( Y \) - axes are assumed to be orientated parallel to the length and width of the beam respectively and \( Z \) - axis is directed upwards perpendicular to the substrate. The critical collapse voltage of the bridge in the simplified one dimensional pull - in model depends on the linear elastic response of the bridge and the gap between the bridge and center conductor. This is based on the consideration of the mechanical forces, electrostatic forces, and residual stress of the bridge. Although not numerically exact, this
model provides a solution to the governing nonlinear equation that is otherwise difficult to solve analytically.

![Figure 5.10 Schematic view of (a) Micromachined capacitive MEMS switch (b) MEMS Bridge modeled as fixed - fixed beam](image)

The governing differential equation for the pull-in instability of a fixed - fixed beam structure incorporating the first order fringing - field correction is derived as

\[
\frac{d^2}{dx^2} \left( E_1 I \frac{d^2 h}{dx^2} \right) - T_b \frac{d^2 h}{dx^2} = P_e(x)
\]

(5.33)

where \( E_1 \) is the effective Young's modulus of the beam, \( I = \frac{wt^3}{12} \), \( T_b = \sigma_1 wt \), \( t \) and \( w \) is the thickness and width of the bridge respectively and \( \sigma_1 \) is the effective residual stress of the bridge. The equivalent distributed load \( P_e(x) \) (Huang et al 2001) resulting from an applied voltage is equivalent to

\[
P_e(x) = -\frac{\varepsilon_0 V^2}{2h^2} \left( 1 + 0.65 \frac{h}{w} \right) \left[ \delta \left( x + \frac{L_2}{2} \right) - \delta \left( x - \frac{L_2}{2} \right) \right]
\]

(5.34)
where \( |x| \leq L_1 / 2 \), \( L_1 \) is the length of the bridge, \( V \) is the applied voltage, \( \varepsilon_0 \) is the permittivity of air, \( L_2 \) is the length of center conductor and \( x \) is the direction of \( X \)-axis. The gap parameter \( h = h(x) \) and stepwise function \( \delta(x) \) are provided by

\[
h(x) = g(x) + \frac{g_1}{\varepsilon_r} \quad \text{and} \quad \delta(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}
\]

(5.35)

where \( g(x) \) is the gap between the bridge and the dielectric layer, \( g_0 \) its initial gap, \( g_1 \) the thickness of the dielectric layer and \( \varepsilon_r \) is the relative permittivity of dielectric layer compared to air.

For a fixed - fixed beam, the effective modulus \( E_f \) is dependent on the beam width. A beam is considered wide when \( w \geq 5t \). Wide beams exhibit plane - strain conditions and therefore, \( E_f \) becomes the plate modulus and it is \( E/(1-v^2) \), where \( E \) is the Young’s modulus and \( v \) the Poisson ratio. A beam is considered narrow when \( w < 5t \) and for this case \( E_f \) becomes the Young’s modulus \( E \). The effective residual stress \( \sigma_i \) is the original biaxial residual stress for bridges while \( \sigma_i \) is \( \sigma (1-v) \) for fixed - fixed beam.

### 5.4.2.2 Effective stiffness constant

The external voltage \( V \) is applied between the bridge and CPW causes the bridge to electrostatically deflect downwards. Deflection increases with voltage until pull - in occurs. When the bridge deflects, the gap between the bridge and electrode varies along the length. Hence the reference value of the gap used for computing the effective stiffness constant is defined as the gap at the location of maximum deflection of the fixed - fixed beam. The effective stiffness constant \( K_{eff} \) measured in N/m\(^3\) is derived from the small-
deflection solution for a partially uniform distributed load \( P \) over the center of the structure divided by the center gap deflection as

\[
K_{\text{eff}} = \frac{P}{d_{\text{max}}} \tag{5.36}
\]

where \( d_{\text{max}} \) is the maximum displacement of the structure with no electrostatic load, but with a uniformly distributed pressure load, \( P \). The analytical 2D solution of the differential equations for the stiffness of the uniformly loaded beam considering the effect of residual stress (Huang et al 2001) is obtained as

\[
K_{\text{eff}} = \frac{8\sigma_1 t}{L_1^3 \left[ (2 - \xi) + (2\xi/\beta)((1 - \coth(\beta))/\sinh(\beta)) - (2/\beta^2)\left(1 - (\exp(1 - \xi))/\beta + \exp(\xi/\beta)(1 + \exp(\beta))\right) \right]} \tag{5.37}
\]

with two normalized parameters \( \xi \) and \( \beta \) being

\[
\xi = \frac{L_1}{L_2} \quad \text{and} \quad \beta = \frac{1}{2} \frac{t}{L_1 \sqrt{E_1 I_t}} \tag{5.38}
\]

If the parameter \( \beta \) is small or the residual stress tends to 0, the effective stiffness constant will tend to or reduce to the approximate linear elastic expression for the stiffness including the residual stress effects, which is expressed as

\[
K_{\text{eff}} = \frac{32E_1 t^3}{L_2 \left( 2L_1^3 - 2L_1L_2^2 + L_2^3 \right)} + \frac{8\sigma_1 t}{2L_1L_2 - L_2^2} \tag{5.39}
\]
5.4.2.3 Critical collapse voltage

The material and geometrical parameters of the considered micromachined capacitive MEMS switch structure are listed in Table 5.3. The equivalent distributed load resulting from an applied voltage namely the equivalent electrical pressure between the bridge and the center conductor has the same units as a pressure (Huang et al 2001) and is equivalent to

\[ P_e(x) = \frac{\varepsilon_0 V^2}{2 h^2} \left( 1 + 0.65 \frac{h}{w} \right) \]  

(5.40)

The total upward force on the bridge is

\[ F(h) = K_{\text{eff}} (h_0 - h) - P_e \]  

(5.41)

where \( h_0 = g_0 + (g_s / \varepsilon_0) \). In static equilibrium \( F(h) = 0 \) and the static equilibrium is stable when \( \partial F / \partial h < 0 \). As the voltage increases, the gap decreases until instability or collapse condition is reached.

The critical collapse gap voltage (Huang et al 2001) is given by

\[ V = \sqrt{\frac{8 K_{\text{eff}} h_0^3}{27 \varepsilon_0 [1 + 0.42 (h/w)]}} \]  

(5.42)

and the critical collapse gap distance \( h_c = \frac{2}{3} h_0 \).
Table 5.3  Material and geometrical parameters of micromachined capacitive MEMS switch

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values with units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Young’s modules ((E_{Au}))</td>
<td>76.52 GPa</td>
</tr>
<tr>
<td>Poisson ratio ((\nu_{Au}))</td>
<td>0.41</td>
</tr>
<tr>
<td>Density (\rho_{Au})</td>
<td>(19.3 \times 10^3 \text{ (Kg/m)}^3)</td>
</tr>
<tr>
<td>Permittivity of air (\varepsilon_0)</td>
<td>(8.854 \times 10^{-12} \text{ F/m})</td>
</tr>
<tr>
<td>Relative permittivity of dielectric layer</td>
<td>7.6</td>
</tr>
<tr>
<td>Length of the bridge (L_1)</td>
<td>280 (\mu\text{m})</td>
</tr>
<tr>
<td>Length of center conductor (L_2)</td>
<td>120 (\mu\text{m})</td>
</tr>
<tr>
<td>Initial gap between bridge and dielectric layer (g_0)</td>
<td>1.5 (\mu\text{m})</td>
</tr>
<tr>
<td>Width of the bridge (w)</td>
<td>90 (\mu\text{m})</td>
</tr>
</tbody>
</table>

5.4.2.4  Effective stiffness constant for complex bridge structures

In order to lower the critical collapse voltage, two complex bridge structures as shown in Figures 5.11 (a) and (b) are being considered. The effective stiffness constant of these structures are calculated with different beam width along their length direction. The effective stiffness constant of these complex bridge geometries would not been calculated directly from Equation (5.35) for they have different beam widths along their length direction.

The complex structure can be simplified to have different inertias (due to different beam widths) for different beam sections. These bridge structures are modeled using a general approach as shown in Figure 5.11 (c) where \(m\) is the section number for the different beam sections.
Figure 5.11 Different geometry for computing effective stiffness constant
(a) Structure 1 (b) Structure 2 (c) General analytical model

With this simplification, the effective stiffness constant is obtained by the approximate solution of the linear elastic equation including the effect of residual stress (Huang et al 2001) expressed as

\[
K_{\text{eff}} = 32E_1t \left[ L_1 \sum \left( \frac{w_1}{w_m}, \frac{w_2}{w_m}, \ldots, \frac{w_{m-1}}{w_m}, \frac{L_2}{L_1}, \frac{L_3}{L_1}, \ldots, \frac{L_{m-1}}{L_1} \right) \right]^{-1} + \frac{8\sigma_1t}{L_1^2g(L_{m-1}/L_1)} \quad (5.43)
\]
where $f$ and $g$ are two normalized functions that are depend on the ratio of the structures, defined as

$$f(b_1, b_2, ..., b_{m-1}; a_2, ..., a_m) = \left( \sum_{j=2}^{m-1} \frac{-6a_{j-1}^2 + 8a_{j-1}^3 + 6a_j^2 - 8a_j^3}{b_j} + \frac{2 + 6a_1^2 - 8a_1^3}{b_1} - \frac{6a_{m-1}^2}{b_{m-1}} + 8a_{m-1}^3 - 2a_m^3 + a_m^3 \right) a_m$$

(5.44)

and

$$g(a_m) = 2a_m - a_m^2$$

(5.45)

The critical collapse voltage $V$ of these bridge structures is also computed with Equations (5.42) and (5.43) for the effective stiffness constant $K_{eff}$.

5.4.3 Theory of Proposed Neural Model

In this research, the MLP has been used as it is powerful in solving engineering problems. The structure and its training are well established, and the model has good generalization capability. An example of using a MLP model can be found in Nassif et al (2013). In feed forward process, the inputs are fed to the first hidden layer and the outputs from the first layer are fed to the neurons in the second layer. The links between the inputs and the hidden layer are the coefficient of weight. The third layer called output layer having single neuron gets its input from all hidden layer neurons.
5.4.3.1 Selection of number of neurons and hidden layers

To determine the number of neurons, repeated simulations are performed with several set of neurons and hidden layers. Too many neurons in hidden layer often contribute to over fitting (Lee et al 2006), while a network with too few neurons may not be able to learn the desired input/output mapping. In practice, neural networks with one or two hidden layers are commonly used for RF / microwave applications. Intuitively, four layer perceptrons would perform better in modeling nonlinear problems where certain localized behavioural components exist repeatedly in different regions of the problem space.

The two hidden layer networks are favoured in pattern classification tasks (Tamura & Tateishi 1997) due to their better mapping capability and superiority over one hidden layer network in terms of the number of parameters needed for the training data. To prove it, the correlation coefficient of one and two hidden layer network is checked. Based on the observation, it is found that higher correlation coefficient (0.9826) is obtained for two hidden layer network when compared to lower correlation coefficient (0.9163) for one hidden layer network.

Since the correlation coefficient is high, a feed forward back propagation network with two hidden layer of 8 neurons in each hidden layers is developed for this work and is shown in Figure 5.12 (a). The tangent activation function for hidden layer and sigmoid algorithm for output layer is used for learning. With the chosen LM algorithm for training, the ANN model converges with MSE of $2.93 \times 10^{-3}$ as shown in Figure 5.12 (b).
Figure 5.12 (a) Proposed neural model for critical collapse voltage calculation (b) Convergence of mean square error with 1000 epochs for training of network

5.4.3.2 Selection of input/output variables

The following training and testing source datasets for the proposed switch geometry are assumed in order to reduce the complexity of neural model:

Width of the beam ($w$) : 90 µm,

Thickness of the bridge ($t$) : 1.5 µm

Thickness of the dielectric layer ($g_1$) : 0.15 µm and

Length of the center conductor ($L_2$) : 120 µm.

The various input and output variables for the ANN model are: length of beam, initial gap and residual stress and critical collapse voltage respectively. All model parameters except the above mentioned are allowed varying and MATLAB simulation is used to generate the datasets. The selected ranges of various inputs are: $0.5 \, \mu\text{m} \leq g_0 \leq 4.5 \, \mu\text{m}$, $100 \, \mu\text{m} \leq L_1 \leq 1100 \, \mu\text{m}$ and $1 \, \text{MPa} \leq \sigma_1 \leq 131 \, \text{MPa}$. For the analysis of critical collapse
voltage, simulated datasets are derived by using all above input data by varying the residual stress, length of center conductor and the gap between the bridge and center conductor since these geometries majorly affect the stability region of proposed geometry.

5.4.3.3 Selection of training algorithms

During training, the network performance is predicted by computing the error as the difference between actual network outputs and MATLAB simulation output for the training samples. The weights are adjusted with the learning rate in order to minimize the error of the network (Wang et al 1998). This process is called a back propagation training algorithm. In order to predict the optimum weight and bias values, several optimization techniques are practiced with the chosen network architecture. The Levenberg - Marquardt (LM), Quasi - Newton (QN) and Conjugate Gradient (CG) for standard gradient based numerical optimization and resilient back propagation for heuristic technique are used. The convergence rate and speed of each algorithm are monitored to choose the best scheme of training of ANN model. The performance rate in terms of MSE for 100 and 1000 epochs are compared for four selected algorithms and given in Table 5.4.

Table 5.4 Comparison of MSE for selected four training algorithms

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100 Epochs</td>
</tr>
<tr>
<td>LM</td>
<td>0.331</td>
</tr>
<tr>
<td>BR</td>
<td>0.957</td>
</tr>
<tr>
<td>CGF</td>
<td>0.904</td>
</tr>
<tr>
<td>RP</td>
<td>0.344</td>
</tr>
</tbody>
</table>
The total of 572 datasets is generated using MATLAB simulation. Among these datasets, 286 training and 52 testing datasets are selected based on cross validation process for the ANN model. After training the network with four algorithms for the entire training datasets in a total duration of 18 minutes, it is found that the convergence rate of LM algorithm is high and it is taken for further training. With chosen LM algorithm, for example, the ANN model took four minutes for training and six seconds for testing with 687 epochs using dual core processor.

5.4.4 Results and Discussion

Figure 5.13 illustrate the generation ability of MLP neural network by depicting the critical collapse voltage of MATLAB simulation and neural network prediction for the training data sets. It is clear from Figures 5.13 (a) & (b) that the critical collapse voltage decreases rapidly as the length of the bridge increases, where it corresponds to the case when the width of the center conductor is kept constant.

This is because of the increase in effective area with the applied voltage pressure. The effect of residual stress in critical collapse voltage has been depicted in Figure 5.13 (c) for three different length (120 µm, 140 µm and 200 µm) of center conductor. Therefore the residual stress has to be minimised during the fabrication process in order to minimise the critical collapse voltage. In the comparison of voltage calculation using analytical solution Equation (5.37) and approximate solution Equation (5.39) for effective dielectric constant as shown in Figure 5.13 (d), the deviation between two graphs shows the error in calculation by approximate solution for effective dielectric constant and corresponding in critical collapse voltage.
Figure 5.13 Comparisons of MATLAB (Solid) and neural (Dashed) output for critical collapse voltage versus length of bridge for various residual stress (a) Using $K_{\text{eff}}$ calculated by analytical 2D solution for the stiffness and b) Using $K_{\text{eff}}$ calculated by approximate linear elastic expression (c) Critical collapse voltage versus residual stress comparison with $K_{\text{eff}}$ calculated by analytical 2D solution (Solid) and $K_{\text{eff}}$ calculated by approximate linear elastic expression (Dashed) (d) Comparison of $V$ with $K_{\text{eff}}$ calculated by analytical 2D solution and approximate linear elastic expression
For optimization, several switch structures have been studied in order to improve the electrical parameters and lower the critical collapse voltage. Two optimum structures as shown in Figures 5.11 (a) and (b) are taken for consideration to reduce the effective dielectric constant, thereby decreasing the critical collapse voltage. Figures 5.14 (a) and (b) show the pull-in simulation result compared with the neural model for structure 1 and 2 respectively. Figure 5.14 (c) denoted the comparison of two structures critical collapse voltage and it is proved that structure 2 is the optimum structure as it has lower critical collapse voltage than structure 1.

Figure 5.14 Comparisons of neural output for critical collapse voltage versus bridge gap for various residual stress (a) Structure 1 (b) Structure 2 (c) Comparison of critical collapse voltage for both structures
Therefore it is inferred that, the critical collapse voltage can be reduced only when the following conditions or threats are met with:

1. Increase in the length of the bridge with constant width of the center conductor.
2. Increase in width of center conductor for a prefixed length of bridge.
3. Controlling of biaxial residual stress well during the fabrication process.
4. Increase in the gap between the bridge and the center conductor.
5. Strong control of material properties and switch geometry

Reduction in critical collapse voltage will ensure the stable operation of micromachined capacitive shunt RF MEMS switch.