

# Chapter 13

## ANN Modeling of Motional Resistance for Micro Disk Resonator

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### ABSTRACT

*This article describes how modeling is an integral part of design and development of any system that provides the theoretical characterization of the system and helps in understanding the relations between various parameters of the system, before the system is developed. The capability of an Artificial Neural Network (ANN) to model the complex relations between a set of inputs and outputs is exploited to model the motional resistance and resonance frequency for a contour mode disk resonator. The solution was to develop a multilayer feed forward neural network. The data set required to train the ANN is obtained by developing an electrical equivalent model and through the MEMS simulation software Coventorware. The network is trained using a Levenberg Marquardt algorithm. The number of hidden layers and the number of neurons in each hidden layer is optimized using a genetic algorithm. The ANN model developed an efficient model of the motional resistance and resonance frequency of the disk resonator. The ANN output is compared with the output of an electrical equivalent model and a reported fabricated structure.*

## 1. INTRODUCTION

Modern wireless communication transceivers operate in various frequency range. Many of the modern-day transceivers operate in GHz range. Resonators are integral part of these transceivers. High level of integration and reconfigurability are the two important requirements of the resonators used in today's wireless transceivers. The various types of resonators used in RF wireless communication are coaxial resonator, dielectric resonator, crystal resonator, ceramic resonator, Surface Acoustic Wave (SAW) resonator and YIG resonator. Out of these the most widely used resonators are quartz crystal resonator and SAW resonators because of their very high-quality factor and very good thermal stability. All though these resonators provide extremely high-quality factor, they are bulky off chip components which are usually integrated at board level making miniaturization a difficult task. One of the important requirement of modern day miniaturized wireless transceivers is on chip integration of all the components. This has made the MEMS resonators a more feasible option for RF wireless communication (Jokic, Frantlovic, Djuric & Dukic, 2015). MEMS resonators have started replacing crystal resonators because of their on-chip integration capability and quality factor comparable with crystal resonators.

A MEMS resonator comprises of some mechanical structure, an input transducer to convert incoming electrical signal into mechanical vibrations and an output transducer to convert the mechanical vibration into electrical signal. To set the structure into motion a DC bias voltage is applied to the structure and AC input voltage is applied to the input electrode. This creates a time varying electrostatic force because of which the structure vibrates. When the frequency of the applied input voltage is equal to the natural frequency of the structure, the structure vibrates with maximum amplitude. In mechanical structures such as cantilever beam, clamped-clamped beam and free-free beam the dominant stress is bending stress and the structures vibrate orthogonally to the bending stress. For these kind of resonators as the dimensions of the structure is scaled to obtain higher resonance frequency, the quality factor decreases. Hence beam type of resonators are not suitable for high frequency and high-quality factor applications. Mechanical structures such as disk and square plate resonators have large stiffness and vibrate in plane because of the formation of longitudinal waves (Sutagundar, Sheeparamatti & Jangamshetti, 2014). Disk resonator is preferred over beam type resonator in high frequency and high-quality factor applications because of its large stiffness (Basu & Bhattacharyya, 2011).

The electromechanical nature of the MEMS resonators makes the design and development of MEMS resonators a challenging task. Modeling is an integral part of design and development of any system that provides the theoretical characterization of the system and helps in understanding the relation between various parameters of the system, before the system is developed. The modeling of resonator requires the understanding of relation between various mechanical and electrical parameter. Conventionally, Finite Difference Time Domain (FDTD) and Finite Element Techniques are the two most widely used modeling techniques. These are numerical techniques which are computationally expensive and are time consuming. ANN, having the capability of extracting the complex relation between various input and output parameters, can be used for modelling of MEMS resonators. The ANNs require a huge amount of training data particularly when the input output relation is non-linear. Obtaining the training data for modeling of disk resonator through simulation or experiments is time consuming and difficult task. Knowledge based artificial neural networks are hybrid networks that use the domain knowledge along with measurement/simulation data to model a system. The empirical equations or an electrical equivalent circuit of the system to be modelled can be used to generate the training data. Because of the theoretical domain knowledge, these ANNs require less amount of training data (Towell & Shavlik, 1994).

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