Neural Network-Based MEMS Failure Probability Prediction

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ABSTRACT

This paper reports a neural network-based methodology for failure probability prediction and quality enhancement of microengine MEMS using attribute data derived from actual measurements on microengines. A backpropagation neural network was employed for failure probability prediction. Microengine attributes constituted the inputs while time-to-failure statistics (mean, median and shape parameters) constituted network outputs. Once neural network training was complete, independent data was used to validate results. Correct prediction of failure statistics was achieved with high confidence (~0.9). Low humidity (0-10%) and high microengine resonant frequency coupled with microengine operation at 0.4 of resonant frequency was found to result in median times-to-failure of at least 200 million cycles – i.e. high reliability.

Keywords: MEMS reliability, neural networks, failure probability prediction

1 INTRODUCTION

Micro-Electronic-Mechanical Systems (MEMS) are a combination of microscopic mechanical elements (sensors, actuators) and microelectronic devices (MOS transistors, capacitors) fabricated on a common silicon substrate. Like their microelectronic counterparts, the micromechanical components are fabricated by using compatible "micromachining" processes that selectively etch away parts of the silicon wafer and add new structural layers. Unprecedented levels of functionality and sophistication can be placed on a small integrated circuit (IC) chip at a relatively low cost because MEMS devices are manufactured using today's cost-effective batch IC fabrication techniques. By augmenting the computational ability of microelectronics with the perception and motion control capabilities of microsensors and microactuators, MEMS technology has permitted development of many "smart" products today. Microsensors embedded in MEMS gather data from the environment by measuring optical, magnetic, mechanical, thermal and chemical stimuli. Microelectronic computational systems within the MEMS process this data and - using inherent decision making capabilities - direct actuators inside the MEMS to respond in specific ways resulting in desired environmental control action such as device re-positioning and process adjustment. Miniaturization makes MEMS attractive within many industries (e.g. automotive and aerospace), additionally, significant reductions in production costs have provided commercial feasibility. Recently, the MEMS market has grown sharply and is now estimated at over $30 billion.

1.1 MEMS Failure Probability Distribution

In all application areas, MEMS quality which impacts robust and reliable operation is a key consideration [1-6]. Quality can be measured in a number of ways two of which are output performance variability and failure probability. The work reported in this paper focuses on the latter metric – a measure of the likelihood of catastrophic failure which typically compromises safety. Historically, the first major MEMS to gain commercial feasibility were accelerometers (pioneered to provide airbag deployment systems) widespread use of which did not take place until Chrysler introduced them in American-made vehicles in 1989. Today, accelerometer MEMS have been observed to exhibit failures, causing accidental deployment of airbags. Another early commercial success was inertial guidance units (IGUs) used in submarines and ballistic missiles. These too have been known to exhibit undesirable drift compromising target safety. Clearly, it is an important part of any development process to estimate and enhance MEMS reliability at the conceptual design phase before devices are actually built. Since MEMS research is still in relative infancy, traditional methods of quantifying reliability are inadequate because devices are not in existence in large volumes and cannot be tested to establish reliability distributions. Since analytic models are also unavailable, MEMS design would benefit immensely from a methodology for estimating reliability based on measurements on a limited population. This paper reports an effective neural network-based approach to MEMS reliability prediction and enhancement. MEMS attributes including fabrication process variables, design characteristics, physical attributes, operating environment and performance are mapped to a failure probability distribution. Several distributions are possible, however, analysis of the microengine failure data revealed that the log-normal distribution - well established for semiconductor device reliability - was the closest fit. Lognormal distributions are typically characterized by 2 parameters – the median time to failure t_{50} and the shape parameter σ. Specifically, this work

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uses the lognormal distribution parameters median t_{50} and shape σ as well as the mean μ to approximate the time-to-failure of microengines. A total of seven microengine attributes are mapped to five lognormal distribution parameters using a multilayer perceptron backpropagation network. Earlier work [7] at Sandia National Labs demonstrated the efficacy of the Error-K neural network in similar predictive role.

2 NEURAL NETWORKS

Artificial neural networks (ANNs) are mathematical constructs loosely modeled on the organizational principles of the animal brain. They are networks of relatively simple processing elements in which global behavior is determined by the strength of connections between elements[11]. Hundreds of neural net paradigms exist today as a result of extensive research, each defined by architecture (e.g. multilayer perceptron MLP) and learning rule (e.g. backpropagation learning). In the work reported here, the MLP network with backpropagation learning – henceforth referred to as backpropagation network - is used. In terms of architecture, a back-propagation network typically has an input layer, an output layer and at least one hidden layer (fig 1). There is no theoretical limit on the number of hidden layers but typically there will be one or two. Each layer is fully connected to the succeeding layer, the arrows indicating flow of information during validation. Back-propagation learning is a technique for solving the credit assignment problem posed by Minsky and Papert in *Perceptron* [8]. In moving from one layer to another, the notation for describing the learning rule is as follows (superscript in square brackets is used to indicate which layer of the network is being considered):

$x_j^{[s]}$ current output state of j^{th} neuron in layer s
$w_{ji}^{[s]}$ weight on connection joining i^{th} neuron in layer (s-1) to j^{th} neuron in layer s
$I_j^{[s]}$ weighted summation of inputs to j^{th} neuron in layer s

A back-propagation element therefore transfers its inputs as follows:

$$x_j^{[s]} = f\left(\sum_i \left(w_{ji}^{[s]} \cdot x_i^{[s-1]}\right)\right)$$

$$= f\left(I_j^{[s]}\right)$$

where f is traditionally the sigmoid function but can be any differentiable function. Backpropagation is a form of supervised learning, a generalization of the least squares algorithm that modifies network weights to minimize the mean squared error between the desired and actual outputs of network. Once trained, the network weights are frozen and can be used to compute output values for new input queries. The forward process involves presenting an input pattern to input layer neurons that pass the input values onto the first layer. Each hidden layer node computes a weighted sum of its inputs, passes the sum through its activation function and presents the result to the output layer. During learning, information is also propagated back through the network and used to update the connection weights.

3. MICROENGINE FAILURE PROBABILTY PREDICTION

Successful development of a neural network to predict microengine reliability requires selection of relevant microengine attributes that have strong correlation with component reliability. Based on experience in [7], eight microengine attributes were selected: *Humidity, Operating Frequency f_o, Resonant Frequency f_r , Ratio f_o/f_r, Spring Quotient, Pin Joint Design, Flexure*. Data on these attributes and the corresponding cycles to failure collected at Sandia National Labs was used. This data - reflecting the performance of 787 tested microengines -was resolved into twenty eight groups, each having similar microengine input attributes. Eleven of the twenty eight groups exhibited a bimodal lognormal distribution for cycles-to-failure (fig 2) characterized by five distinct parameters: *mean μ, lower shape parameter* σ_L, *lower median time-to-failure* t_{L50}, *upper shape parameter* σ_U and *upper median time-to-failure* t_{U50}. The remaining seventeen groups exhibited unimodal lognormal distributions (fig 3) and were treated as special cases of bimodal distributions having identical upper and lower shape ($\sigma_U = \sigma_L$) and median time-to-failure ($t_{U50} = t_{L50}$) parameters. The range of attributes and cycles-to-failure statistics observed for the 787 microengines was

Inputs:
(a) Humidity: 0% to 70%
(b) Operating Frequency f_o: 860hz to 3000hz
© Resonant Frequency fr: 8394Hz to 10608Hz
(d) Ratio f_o/fr : 0.081 to 0.273
(e) Spring Quotient: 1804 to 1825
(f) Pin Joint Design 0,1
(g) Flexure Design 0, 1

Outputs (# of operating cycles to failure):

(a) Mean	1.01e+05 to 7.53E+08
(b) Upper σ_U	6.95E+031 to 1.72E+09
© Lower σ_L	3.20E+04 to 6.62E+08
(d) Upper t_{U50}	1.40E+04 to 1.72E+09
(e) Lower t_{L50}	1.40E+04 to 6.62E+08

Several backpropagation network configurations were tested to determine the best topology for microengine failure probability prediction. The 7-6-5 network topology with single hidden layer of 6 nodes was found to perform best. A learning coefficient of 0.15 for the output layer and 0.3 for the hidden layer with a momentum factor of 0.4 was used. Database was partitioned into training (80%) and test (20%) data and following 40,000 cycles of training an rms training error of 0.07 and test error of 0.08 was obtained. Figures 4 and 5 are typical scatter plots of actual versus predicted pdf parameters for median time-to-failure and shape parameter σ for test data. These plots confirm the fact that the backpropagation neural network successfully predicted lognormal statistics which were consistent with the test data. The r^2 values obtained for failure probability parameters consistently exceeded 0.92 indicating a high degree of correlation between actual and predicted parameters. Additionally, sensitivity information – available from the neural network as a by product - provided valuable insight for reliability enhancement indicating that the most sensitive microengine attributes are humidity, operating frequency f_o and f_o/fr ratio (see attribute refinement below).

4. CONCLUSIONS & FUTURE WORK

Neural networks provide an important mechanism for correlation of MEMS attributes to failure probability statistics. Additionally, neural networks have been used to identify desirable MEMS attributes for high reliability thereby permitting microengine design refinement in a systematic way. The results are fully applicable to the design of any MEMS including today's accelerometers, steerable micromirrors and piezo-actuators. In future work, a larger database having greater resolution of attributes will be employed in order to achieve better tracking of the attribute/reliability surface. MEMS attributes will be sampled on a Monte Carlo basis to provide better coverage of the multidimensional attribute design space. Alternative neural network architectures and learning rules will be investigated, in particular the modular neural network [9-10] successfully applied by the authors to the spiral inductor and circuit interconnect layout optimization problem.

5. Bibliography

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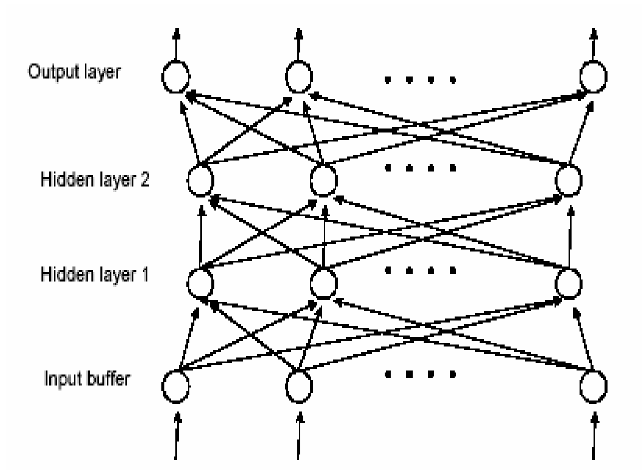

Figure 1 Backpropagation Network

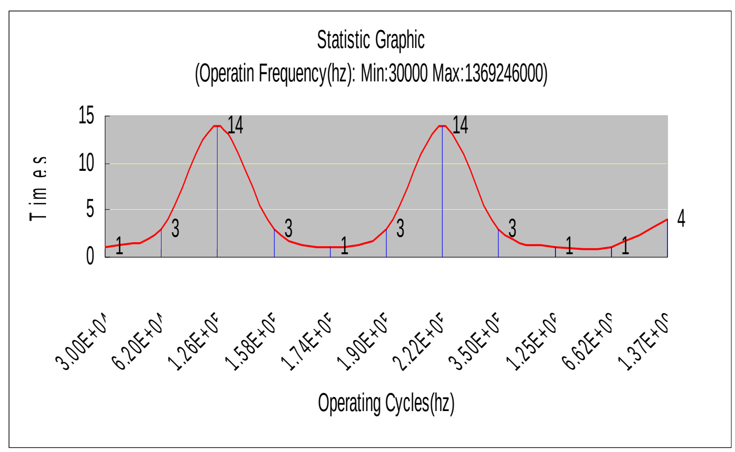

Fig 2 Typical BiModal Distribution for Microengine Cycles-to-Failure

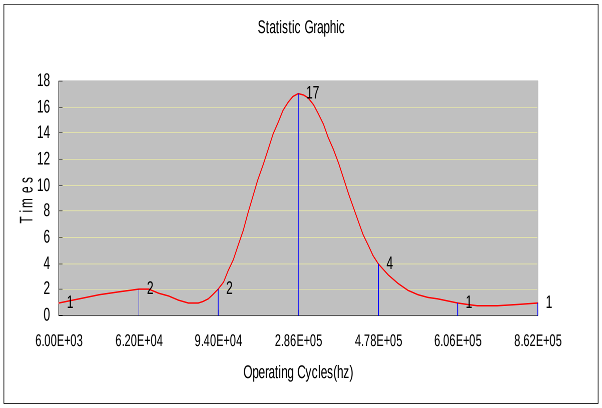

Fig 3 Typical UniModal Distribution for Microengine Cycles-to-Failure

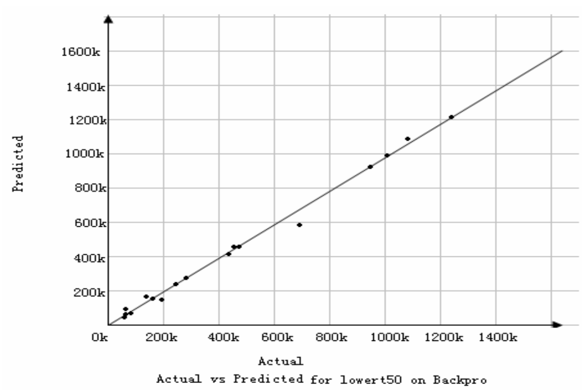

Fig 4 Actual versus Predicted Microengine t_{L50} parameter

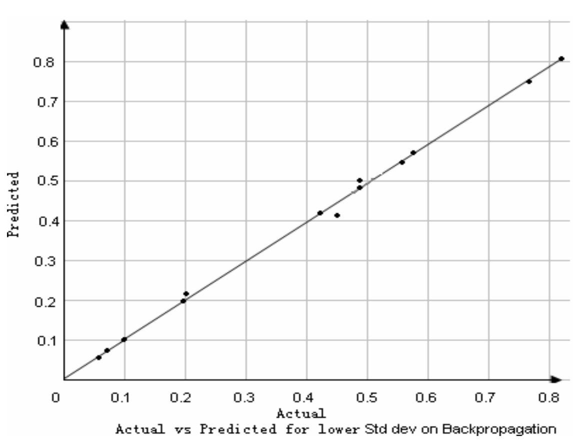

Fig 5 Actual versus Predicted Microengine σ_L parameter (x 1E-8)