Magnetic Nanocomposite Materials for RFID and RF Passives Miniaturization

Lara Martin¹, #Daniela Staiculescu², Haiying Li¹, S.L. Ooi¹, C. P. Wong², M.M. Tentzeris²
¹Motorola, Plantation, FL, 33322, U.S.A.
²Georgia Institute of Technology, Atlanta, GA, 30332, U.S.A.

1. Introduction

The inception of RFID (radio frequency identification) has enabled contactless transfer of information without the requirement of line of sight association, specifically between a reader and transponders that reside on an identified item. As the technology for RFID systems developed, there has been a need to design more flexible systems enabled at the transponder, namely miniaturization of the transponder and ability to tune system performance to accommodate EM (electromagnetic) absorption and interference from surrounding media [1]. Three-dimensional transponder antennas that utilize wound coil inductors do make use of magnetic cores, but magnetic materials for two-dimensional embedded planar antennas have not yet been successfully realized for standard use. As their three-dimensional counterparts, two-dimensional embedded antennas can reap the same benefits from magnetic materials.

One of the most significant challenges for applying new magnetic materials is understanding the interrelationships of the new materials, design, and performance. In previous studies, it can often be cited that the objectives of miniaturization and improved performance are limited by the limited availability of materials that possess the required properties [2]. Recently, formulation of nano-size ferrite particles has been reported [3] and formulation of magnetic nanocomposites comprised of ferrite filler and organic matrix has been demonstrated [4].

In this study, a benchmark structure is first designed in an EM simulator with the assumptions for an unfilled silicone substrate, followed by physical realizing and testing the structure to ensure agreement with simulation. Then, the EM simulator results, which assume material property variables of a magnetic nanocomposite and geometric design variables, are incorporated into the Design of Experiments (DOE) and Response Surface Method (RSM) statistical optimization techniques, which give a thorough understanding of the system and, most importantly, give information such as how the electrical performance is affected and how they could enhance the capability for miniaturization. Previous work [5] shows successful use of hybrid statistical techniques in microwave system analysis and optimization, but this is the first reported work on incorporating the material properties into the design process. This methodology enables the designer to investigate a system of parameters that include material properties and design geometries for the structure simultaneously and weigh tradeoffs instantaneously, thereby developing an in-depth understanding of the implications that new materials have on design.

2. Benchmarking structure

Without loss of generality, the choice of the benchmarking structure was a short-circuited quarter-wavelength rectangular patch antenna for RFID UHF band (400 – 930 MHz). The initial structure was designed for the lower end of the UHF spectrum and was modeled using HFSS full wave EM (electromagnetic) software. The initial substrate was pure silicone ($\varepsilon_r = 2.65$ and $\tan\delta = 0.001$) of 1.6 mm thickness, and the structure showed a resonant frequency of 385 MHz for a 110mm x 110 mm short-circuited patch dimension.

To begin the optimization, the hybrid EM simulation/statistical tools methodology was applied to quantify the effect of material properties and geometries on the performance of the benchmarking structure. The chosen statistical tool was full factorial DOE with center points [6].
designs are used in experiments involving several factors, where the goal is the study of the joint
effects of the factors on a response. The $2^k$ factorial design is the simplest one, with $k$
factors at 2
levels each. It provides the smallest number of runs for studying $k$ factors and is widely used in
factor screening experiments [6]. Center points are defined at the center of the design space and
increase the capability of investigating the validity of the model, including curvature in the response
and accounting for variation in the fabrication process of the structure. Since the statistical models
are based on deterministic simulations, the variation of the center points was statistically simulated.
Specifically, center points were randomly generated assuming a mean equal to the exact center
point value and variation expected in a typical fabrication process. For the expected variations, $3\sigma$
fabrication processes were assumed for stated tolerance capabilities.

For the DOE, the parameters under investigation as input variables were $\varepsilon_r$ (relative permittivity),
$\mu_r$ (relative permeability) and $d$ (inset length). Although not included as an input for the initial
DOE, $w$ (microstrip width) was simulated separately to ensure $50\,\Omega$ impedance matching, depending
on values for $\varepsilon_r$, $\mu_r$, and $h$ for the different experimental conditions. The antenna dimensions
included as input variables are shown in Fig. 1, with $h = 0.2\,\text{mm}$.

The design space for the input variables was chosen such that it includes values of an actual
magnetic nanocomposite material that has been formulated and incorporates fabrication limitations
and design rules for the dimensions. The ranges for the input variables for the initial DOE are
presented in Table 1 and the tolerance capabilities used to simulate center point variability are as
follows: +/- 0.15 for $\varepsilon_r$ and $\mu_r$ and +/- 0.3 mm for $d$. The output variables, or responses, for the DOE
were the resonant frequency $f_{res}$ and the corresponding return loss $RL$.

![Fig. 1. Antenna dimensions](image)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Low value</th>
<th>High value</th>
<th>Center point</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon_r$</td>
<td>2.5</td>
<td>6.5</td>
<td>4.5</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>1</td>
<td>6.5</td>
<td>3.75</td>
</tr>
<tr>
<td>$d$ (mm)</td>
<td>3</td>
<td>9</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 1. Ranges for the input variables.

Once the responses were obtained for the experiment, the best fitting first order statistical model
was determined. Next, the fit was investigated for ultimate lack of fit. An ultimate lack of fit can
arise from curvature in the response or increased variation of fit at one end of the model, for
example. In cases that curvature in the response is detected, the analysis may be extended to
additional axial points indicated by the RSM method, which can account for curvature through
second order model development. Usually, these second order models are reasonable
approximations of the true functional relationship over relatively small regions. Once validated

![Fig. 2. Methodology used for optimization](image)
using statistical diagnostic tools, the models approximate the actual system within the defined design space. This methodology used for the optimization is presented as a flowchart in Fig. 2.

3. Statistical analysis

From the DOE, first order statistical models were developed. The first order model for $f_{res}$ showed to have poor fit, and the first-order model for $RL$ showed to have reasonable fit. Upon inspection of the statistical diagnostic tools used to validate assumptions of normality and equal variance, curvature was detected for $f_{res}$. Even with the detected curvature, the model for $f_{res}$ was statistically significant at the 95% confidence level. The first order model for $RL$ was also statistically significant at the 95% confidence level.

Continuing with the optimization methodology, a second order model was developed using RSM to account for the detected curvature in $f_{res}$ [6]. The second order model for $f_{res}$ was statistically significant at the 95% confidence level. The developed model included the terms $\varepsilon_r$, $\mu_r$, and the interaction $\varepsilon_r \mu_r$. The curvature was alleviated by including the second order terms $\varepsilon_r^2$ and $\mu_r^2$. Additionally, there was significant lack of fit at the 95% confidence level. Although the equal variance assumption could not be validated, the normality assumption was validated. The model for $f_{res}$ is given by (1).

![Mathematical expression]

The developed statistical model for $RL$ from the RSM included the term for $d$ only. The model was further analyzed, and the assumptions of normality and equal variance were validated. Additionally, there was no significant lack of fit at the 95% confidence level. The model for $RL$ is given by (2).

![Mathematical expression]

Before accepting (1) and (2) as the final models, the models had to be confirmed. The confirmations of the models were performed for the following combination of parameters: $\varepsilon_r = 5.1$, $\mu_r = 2.9$, and $d = 4.7$ mm. This combination of input variables was simulated in the EM simulator and was also predicted with the developed models. The results of the simulation compared to the 95% confidence intervals defined by the lower and upper bounds for the predicted $f_{res}$ and $RL$ are as follows: for $f_{res}$, the confidence interval is between 160.2 and 179.6 MHz and the simulated value is 171.4 MHz, while for the $RL$ the interval is between -22.1 and -11.0 dB and the simulated value is -14.5 dB. Because the simulation values fall into the 95% confidence intervals, the models were confirmed. With this confirmation, the models given by (1)-(2) were accepted as the final models.

4. Model interpretation and application

The final step in the study was applying measurements of a fabricated magnetic nanocomposite material to the models. The material was formulated from Dow Corning Sylgard 184 silicone and Steward NiZn ferrite powder #72599. A 40 vol% ferrite paste was produced with a mixer at 240 rpm and 110°C for 30 minutes. The paste was transferred into a flat mold and vacuum cured with a hold confirmed to occur at >125°C for 50 minutes to produce a 1.6 mm thick substrate.

The material was measured using an HP4291A impedance analyzer with material fixtures 16453A for $\varepsilon_r$ and 16454A for $\mu_r$. There were 5 measurements taken for each $\varepsilon_r$ and $\mu_r$. The summary statistics including the mean and 95% C.I. (confidence intervals) for $\varepsilon_r$ and $\mu_r$ are given in Table 2. Based on these results, the values used in the model were $\varepsilon_r = 6.3$ and $\mu_r = 4.4$. 

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According to the model, $RL$ is minimized when $d$ is minimized. To minimize $RL$, $d$ was set equal to 4. With these values for $\varepsilon_r, \mu_r,$ and $d$, the model predicted $f_{res} = 122$ MHz and $RL = -17.5$ dB. The surfaces of the possible solutions from the statistical models are shown in Fig. 3.

Comparing substrates, the shift down in frequency from $f_{res} = 385$ MHz for the pure silicone substrate to 122 MHz for the magnetic nanocomposite substrate proves the miniaturization concept (by a factor $385/122 \approx 3.2$). Similar benefits can be observed for other large-size RF passives, such as integrated RF inductors, that potentially play a critical role in the size of integrated RF modules.

<table>
<thead>
<tr>
<th>Mean</th>
<th>Lower CI</th>
<th>Upper CI</th>
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<tbody>
<tr>
<td>$\varepsilon_r$</td>
<td>6.332</td>
<td>6.227</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>4.252</td>
<td>4.249</td>
</tr>
</tbody>
</table>

Table 2. Mean and 95% confidence intervals for $\varepsilon_r$ and $\mu_r$

Fig. 3. Surfaces of possible solutions for optimized $f_{res}$ and $RL$.

5. Conclusions

A combination of electromagnetic and statistical tools (DOE and RSM) has been used to investigate the impact of magnetic nanocomposite materials to the miniaturization of RFID antennas and RF passives considering geometric, material and fabrication parameters and uncertainties. This approach has been applied to the design of a benchmarking microstrip patch antenna and has enabled the assessment of implications that materials have on this design. The experiment was simple to implement and provided a thorough understanding of the issues to be confronted in the design process. The statistical analysis provided equations to quantify the effect of material properties on the electrical figures of merit, which can relate to the capability for miniaturization. By extending this approach to carefully investigate the behavior of a complete modules and package and including additional parameters, such as the overall structure size and the material loss variation with frequency, the designer can save a lot of time, shorten the design cycle of added functions, and optimize designs in a simple and elegant manner and with a profound understanding of how all these aspects are affecting each other. In addition, this approach could provide a very simple way to determine a-priori confidence levels for component and system performance considering variations of fabrication processes and uncertainties/tolerances in the characterization of exotic novel materials, such as nanocomposites.

References