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Accurate modelling of lossy SIW resonators using a neural network residual kriging approach

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Abstract: In this paper, a computational intelligence method to model lossy substrate integrated waveguide (SIW) cavity resonators, the Neural Network Residual Kriging (NNRK) approach, is presented. Numerical results for the fundamental resonant frequency f_r and related quality factor Q_r computed for the case of lossy hexagonal SIW resonators demonstrate the NNRK superior estimation accuracy compared to that provided by the conventional Artificial Neural Networks (ANNs) models for these devices.

Keywords: CAD, artificial neural networks, kriging, lossy SIW resonators

Classification: Microwave and millimeter-wave devices, circuits, and modules

References

[1] M. Bozzi, *et al.*: "Review of substrate integrated waveguide (SIW) circuits and antennas," IET Microw. Antennas Propag. **5** (2011) 909 (DOI: 10.1049/iet-map.2010.0463).

[2] S. Nam, *et al.*: "Low-cost high-performance frequency-tunable substrate-integrated waveguide filter structure and fabrication method," IEICE Electron. Express **13** (2016) 20160211 (DOI: 10.1587/elex.13.20160211).

[3] G. Amendola, *et al.*: "Computation of the resonant frequency and quality factor of lossy substrate integrated waveguide resonators by method of moments," Prog. Electromagn. Res. Lett. **40** (2013) 107 (DOI: 10.2528/PIERL13031808).

[4] G. Angiulli: "Design of square substrate waveguide cavity resonators: compensation of modelling errors by support vector regression machines," Am. J. Appl. Sci. **9** (2012) 1872 (DOI: 10.3844/ajassp.2012.1872.1875).

[5] G. Amendola, *et al.*: "Characterization of lossy siw resonators based on multilayer perceptron neural networks on graphics processing unit," Prog. Electromagn. Res. C **42** (2013) 1 (DOI: 10.2528/PIERC13051001).

[6] G. Amendola, *et al.*: "Empirical relations for the evaluation of the resonant frequency and quality factor of the TM_{010} mode of circular substrate integrated waveguide (SIW) resonators," Prog. Electromagn. Res. C **43** (2013) 165 (DOI: 10.2528/PIERC13073102).

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[7] M. R. Sunny, *et al.*: "An artificial neural network residual kriging based surrogate model for curvilinearly stiffened panel optimization," Adv. Comput. Des. **1** (2016) 235 (DOI: 10.12989/acd.2016.1.3.235).
[8] M. L. Stein: *Interpolation of Spatial Data: Some Theory for Kriging* (Springer, 1999).
[9] G. Angiulli: "On the computation of nonlinear eigenvalues in electromagnetics problems," J. Electromagn. Waves Appl. **21** (2007) 527 (DOI: 10.1163/156939307780616838).
[10] S. Lophaven, *et al.*: "DACE - A MATLAB Kriging Toolbox," Technical University of Denmark, (2002) http://www2.imm.dtu.dk/projects/dace/.

1 Introduction

Nowadays the substrate integrated waveguide (SIW) technology plays a fundamental role for building effective microwave devices operating at millimeter and sub millimeter bands [1]. A lot of these devices are based on the working principles of cavity resonators [1, 2]. Cavity SIW resonators are microstrip-like structures having walls realized by cylindrical metallic vias [1]. In [3] an effective method to handle cavity SIW with losses, based on the dyadic Green's function of the lossy parallel plate waveguide, has been presented. To reduce the computational burden associated with the design and the optimization of these devices in [4, 5, 6] several surrogate modelling technique able to estimate the fundamental resonant frequency f_r and the related quality factor Q_r for these structures, have been exploited. In this paper, an accurate methodology named Neural Network Residual Kriging (NNRK) approach [7] is investigated, in order to develop more accurate surrogate models for lossy SIW cavities. NNRK is a surrogate modelling procedure, intensively used in Geostatistic, Aerospace engineering and Civil engineering [7], to which a little attention has been paid, at the best of the authors knowledge, in the field of the microwave and millimeter wave SIW engineering. It consists in a two step algorithm that couples an Artificial Neural Network (ANN) with a Kriging technique [8], obtaining in this manner a notable improvement of the ANN estimation performances [7]. To demonstrate the NNRK modelling capability, numerical results relevant full wave computations carried out for the case of hexagonal lossy SIW resonators, NNRK and conventional ANNs estimations, are presented and discussed.

2 Computation of resonances and quality factors for a lossy SIW resonator

In this section we concisely recall the main notions concerning the computation of the resonances f_r and the related quality factors Q_r for lossy cavity SIW resonators. As stated in [3], the electromagnetic field inside a lossy SIW cavity can be evaluated by using the dyadic Green's function of the lossy parallel plate waveguide (PPW), and considering the scattering phenomenon due by the metallic via holes realizing the walls of the resonator. The scattered field can be represented by means of suitable cylindrical vector wave eigenfunctions $\mathbf{M}_n$, $\mathbf{N}_n$ [3] having unknown coefficients $A^{TE}_{m,n,l}$ ($A^{TE}_{m,n,l}$) (the apex *TM* and *TE* indicate the *TM* and

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the TE scattered field inside the PPW, respectively). The expansion coefficients $A^{TM}_{m,n,l}$ ($A^{TE}_{m,n,l}$) are determined through the solution of the following matrix linear system [3]

$$\mathbf{L}^{Fd}\mathbf{A}^{Fd} = \mathbf{\Gamma}^{Fd} \quad Fd \in \{TE, TM\} \tag{1}$$

which arises by imposing the impedance boundary condition on the surfaces of each via hole realizing the cavity walls [3]. Cavity resonances f_r are the real part of the complex frequencies $\bar{f}_r$ for which (1) admits a non-trivial solution when the second member is equal to zero [9]. Once that a $\bar{f}_r$ has been located, the related quality factor Q_r can be easily computed as [3]

$$Q_r = \frac{\mathrm{Re}(\bar{f}_r)}{2\,\mathrm{Im}(\bar{f}_r)} \tag{2}$$

3 Regression kriging and neural network residual kriging approach

In the framework of the regression Kriging, the relationship between the input vectors $\{\mathbf{x}^{(i)}\}_{i=1}^{N} \in \mathbb{R}^n$ and the observed responses $\{y(\mathbf{x}^{(i)})\}_{i=1}^{N} \in \mathbb{R}$ is assumed of the form [8]

$$y(\mathbf{x}^{(i)}) = f(\mathbf{x}^{(i)}) + v(\mathbf{x}^{(i)}) \tag{3}$$

where $f(\cdot)$ is a suitable noise free function which models the global input-output behavior, and $v(\cdot)$ is a stochastic process which models the deviation from $y(\cdot)$ of $f(\cdot)$. The process $v(\cdot)$ is characterized by a mean $\mu = 0$, a variance σ^2 and by covariance matrix $\mathbf{C} = \sigma^2\mathbf{\Psi}$, where $\mathbf{\Psi}$ is the correlation matrix [8]. Several functional forms for the $\mathbf{\Psi}$ elements are possible, but in what follows we consider a Gaussian correlation functional form [8], i.e.

$$\Psi_{ij} = \exp\left(-\sum_{l=1}^{N}\theta_l|x_l^{(i)} - x_l^{(j)}|^2\right) \tag{4}$$

In (4) the term $x_l^{(i)}$ ($x_l^{(j)}$) stands for the l-th, component of the i-th (j-th) input vector $\mathbf{x}^{(i)}$ ($\mathbf{x}^{(j)}$), whereas the terms $\theta_l, l \in \{1, \ldots, N\}$ are N unknown parameters, which describe the degree of correlation existing among the components of the input vectors $\mathbf{x}^{(i)}$ and $\mathbf{x}^{(j)}$. Once that the optimum coefficients $\hat{\theta}_l$ have been evaluated solving a suitable maximization problem defined on the input-output data [8], the observed response $y(\mathbf{x}^{(N+1)})$ at a new input point $\mathbf{x}^{(N+1)}$ can be obtained as [8]

$$y(\mathbf{x}^{(N+1)}) = \hat{\mu} + \mathbf{r}^t\mathbf{\Psi}^{-1}(\mathbf{y} - \mathbf{1}\hat{\mu}) \tag{5}$$

In (5) $\hat{\mu}$ is the mean value evaluated using the prior values of the coefficients $\hat{\theta}_l$, $\mathbf{y}$ is the vector of the N observed responses, $\mathbf{r}^t$ is the transpose vector containing the correlation between the new input vector $\mathbf{x}^{(N+1)}$ and the preceding $\{\mathbf{x}^{(i)}\}_{i=1}^{N}$ input vectors, and finally $\mathbf{1}$ indicates the vector having all components equal to 1. The Kriging model defined by (5) can be coupled with an ANN, so as to enhance the accuracy of the output response of this latter without compromising the overall computational cost, thus by realizing the so-called Neural Network Residual Kriging (NNRK) approach (see [7] and references within). NNRK is basically a two step algorithm. Let be $\mathsf{TS} = \{\mathbf{x}^{(i)}, y_i\}_{i=1}^{N}$ a training set built with the aim to develop a surrogate model for a device by an ANN. The first step of the NNRK

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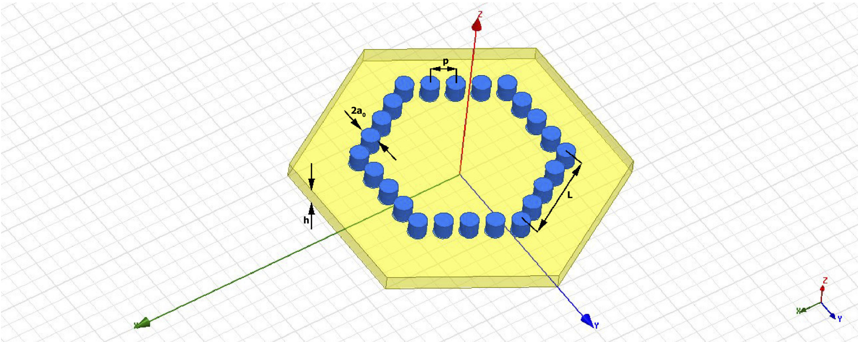

Fig. 1. A hexagonal SIW resonator.

procedure simply consists to train the ANN by using TS. Let be POV $= \{\bar{y}_i\}_{i=1}^{N}$ the set of the ANN estimated outputs related to the input training points $\{\mathbf{x}^{(i)}\}_{i=1}^{N}$. Using POV, the set of residuals SR $= \{\rho_i = \bar{y}_i - y_i\}_{i=1}^{N}$ is formed. The second step of the NNRK procedure simply consists to assemble the new set NTS $= \{\mathbf{x}^{(i)}, \rho_i\}_{i=1}^{N}$, and by using it to build the Kriging model (5). After completing this last step, the NNRK output response in correspondence of a new input point $\mathbf{x}^{(N+1)}$ is simply obtained by adding to the ANN response $\bar{y}_{N+1}$ the residual ρ_{N+1} given by (5) evaluated at $\mathbf{x}^{(N+1)}$ [7].

4 Numerical results

To demonstrate the modelling capability of the NNRK approach, lossy SIW resonators having hexagonal geometry have been considered (see Fig. 1). As specified by the first step of the NNRK procedure, several feed forward multilayer perceptron neural networks configurations have been developed exploiting MATLAB and validated using as performance index the mean square relative error (MSRE) [4, 5]. The following backpropagation rules have been employed: *i*) Polak-Ribiere Conjugate Gradient (PRCG), *ii*) Resilient Backpropagation (RB), *iii*) Gradient Descent (GD), *iv*) Scaled Conjugate Gradient (SCG) [5]. The via hole radius a_0, the pitch p, the substrate thickness h, the dielectric constant ϵ_r, the dielectric loss tangent $tan(\delta)$, the metal conductivity σ_m and side L have been the selected input parameters for the neural architectures, while the fundamental resonant frequency f_r and the related quality factor Q_r have been the outputs.

For these inputs, a range of values of practical engineering interest have been considered. These ranges are reported in Table I. Three set of data, one of training and the others of validation and testing, having 1280, 128, and 128 tuples, respectively, have been created by means of a full wave code based on the theory presented in [3]. The time required to generate these data was about 8 hours on an Intel Xeon DP E5405 Quad Core 2.0 GHz based workstation, with 20 GB of main memory. In term of MSRE (this parameter has been computed with reference to the validation set) the best result has been obtained by a neural architecture having three hidden layers with eight, six and three neurons, respectively, trained by using the RB method (MSRE $\approx 1.42 \cdot 10^{-1}$). Accordingly, as specified by the second step of the NNRK procedure, for this neural architecture we have computed (by using the validation set) the set of residuals SR, which has been exploited to build

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Table I. Range of values for the inputs (all dimensions are in millimeters, σ_m is in Siemens/meter).

a_0	$0.05 \div 0.8$
p	$0.1 \div 2.5$
h	$0.45 \div 0.85$
L	$3 \div 10$
ϵ_r	$2 \div 8$
$tan(\delta)$	$0.015 \div 0.045$
σ_m	$4.8 \cdot 10^7 \div 5.8 \cdot 10^7$

Table II. MSRE computed on the test set.

Method	MSRE
NNRK	$1.24 \cdot 10^{-2}$
ANN	$3.87 \cdot 10^{-1}$

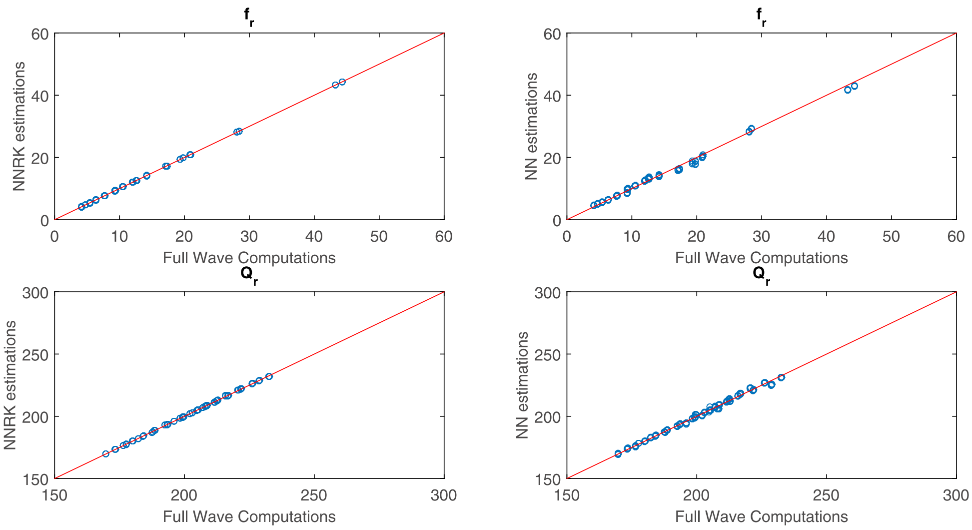

Fig. 2. Scatterer plots. On the right: ANN estimations vs full wave computations (top: f_r scatter plot, bottom: Q_r scatter plot). On the left: NNRK estimations vs full wave computations (top: f_r scatter plot, bottom: Q_r scatter plot).

the Kriging model. To this end, the DACE Kriging toolbox has been used [10]. In Table II the MSRE computed on the test set for the NNRK and for the ANN acting alone, is reported. Fig. 2 shows the scatter plots obtained comparing the values of f_r and Q_r belonging to the test set against those estimated by *i*) the NNRK approach, and *ii*) by the ANN acting alone, respectively. From these results it can be clearly noticed as the NNRK approach gives far better results than compared with those gives by the ANN acting alone (being the MSRE for the NNRK case lower than for the ANN case, we have that the NNRK estimates are less scattered than the ANN estimates, and then more accurate). As a further result, a comparison between the values of the fundamental resonant frequency f_r and the related quality factor Q_r for the hexagonal SIW resonator presented in [3] and those

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estimated by NNRK and by ANN, is reported in Table III. The far lower percentage errors δ_{f_r} and δ_{Q_r} provided by NNRK confirms the better accuracy of this approach.

Table III. Fundamental resonant frequency f_r and quality factor Q_r for the lossy hexagonal SIW resonator presented in [3], values estimated by the developed NNRK and by the ANN acting alone, and related percentage errors δ_{f_r}, δ_{Q_r}.

	f_r	Q_r	δ_{f_r}	δ_{Q_r}
from paper [3]	10.13 GHz	255.4	-	-
NNRK	10.12 GHz	255.1	0.19%	0.12%
ANN	9.98 GHz	251.4	1.48%	1.56%

5 Conclusions

In this paper, an accurate procedure to build surrogate models of lossy SIW cavities which combines ANNs with Kriging, the NNRK approach has been presented. To validate its performances NNRK has been applied to estimate the fundamental resonant frequency f_r and the related quality factor Q_r in the case of lossy hexagonal cavity SIW structures. Numerical results demonstrate the potentiality of the NNRK approach for the development of accurate CAD surrogate models to employ to optimize in a fast way microwave and millimeter wave SIW devices.

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