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***Abstract*— In this paper, the performance of four machine learning regressions like Support Vector Machine (SVM), Least Square-Support Vector Machine (LS-SVM), Gaussian Process Regression (GPR) and Random Forest method (RF) are investigated by means of an illustrative example referring to the characteristic impedance of a microstrip line in terms of electrical and geometrical parameters. The required dataset for training is obtained from a set of parametric electromagnetic simulations. The performance comparison of the four methods is done in the presence and absence of numerical noise and inaccuracies affecting the training samples. The results of our comparison provide a guidance for the proper method selection to model the electromagnetic characteristics of interconnects for high-speed signals: advantages and drawbacks of each of the proposed techniques clearly emerge from this analysis.**

***Keywords*— Microstrip, Support Vector Machine, Least Square, Random Forest, Gaussian Regression.**

I. INTRODUCTION

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Machine Learning (ML) techniques and tools are becoming increasingly important in industry. For the case of supervised learning, these methods can be useful to solve problems for which no analytic solutions exist, by relying on a set of available input and output observations of a generic system. Such data, usually referred as training data, can be used to construct an empirical closed form model approximating the actual nonlinear behaviour of the system. The power of learning algorithms is that the entire process of determining the most likely function that explains the data and makes a prediction on future data combinations is fully automated.

In recent years, learning based methods like support vector machine (SVM) [1], least-squares support vector machine (LS-SVM) [2], random forest (RF) [3] and Gaussian process regression (GPR) [4] have attracted the extensive attention in the electronic and electromagnetic applications, because they allow building compact parametric surrogate models of the output of a generic nonlinear system response with respect to several input parameters [5].

In this work, we consider the modelling of the characteristic impedance of a microstrip line as a function of 4 parameters as an illustrative example to investigate the accuracy and the effectiveness of the above ML regressions. It is well-known that the final response of a microwave structure is sensitive to its geometrical and electrical parameters [6]. In microstrip-based apparatus, like filters, couplers etc, the characteristic impedance plays an important role in the design procedure, especially for interdigital capacitance and stub inductance. Hence, it is essential to accurately predict the system characteristics during the early design phase. Many analytical equations are introduced in the literature for a quick estimation of characteristic impedance of a microstrip transmission line [7-8]. Although these equations have good accuracy, they require pre-calculation of effective dielectric constant. Also, these expressions are valid only for specified interval of geometrical parameters like the ratio of strip width to substrate height. In addition, in many of these formulas, the effect of the frequency is ignored and the conductor thickness is not taken into account. The proposed analysis relies on the dataset available in [9], in which a series of simulation results performed in Sonnet's suite is considered. The simulation results cover a wide range of microstrip parameters such as substrate height, relative dielectric permittivity, strip's width and frequency. Then, the mentioned learning algorithms are applied to the training dataset to create a suitable model of the characteristic impedance. In the following, the test dataset is used to evaluate the generated model. Finally, this work ends with a comparison among the obtained results.

II. MACHINE LEARNING REGRESSION APPROACHES

Let us assume that there is a set of L training samples $D = \{(\mathbf{x}_i, y_i)\}_{i=1,\dots,L}$, where $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$. The goal is to find a nonlinear surrogate model such that.

$$y_i \approx M\left(\mathbf{x}_i\right), \quad i = 1,\dots,L \tag{1}$$

1) SVM Regression

The SVM regression is an advance ML regression which in its primal space formulation writes

$$M_{SVM}\left(\mathbf{x}\right) = \left\langle \mathbf{w}, \boldsymbol{\varphi}\left(\mathbf{x}\right)\right\rangle + b \tag{2}$$

where $\boldsymbol{\varphi}$ is a vector collecting the basic functions, $\mathbf{w}$ is a vector collecting regression unknowns and b is the bias term, respectively.

For the SVM regression, the regression unknowns are estimated by minimizing the so-called ε-intensive loss function and by keeping the model (i.e., by minimizing L2 norm of the coefficient vector $\mathbf{w}$). Thanks to the kernel trick, the above interpretation of the SVM regression, called primal space formulation can be rewritten in its equivalent dual form as follows.

$$M\left(\mathbf{x}\right) \approx M_{SVM}\left(\mathbf{x}\right) = \sum_{i=1}^{L} (\alpha_i - \alpha_i')K\left(\mathbf{x}_i, \mathbf{x}\right) + b \qquad (3)$$

Where $\alpha_i, \alpha_i' \in [0, \mathrm{C}]$ are the pertinent Lagrange multipliers and $b \in \mathbb{R}$ is the bias term, whilst K(.,.) is the he kernel function defined as.

$$K\left(\mathbf{x}_i, \mathbf{x}_j\right) = \left\langle \boldsymbol{\varphi}\left(\mathbf{x}_i\right), \boldsymbol{\varphi}\left(\mathbf{x}_j\right) \right\rangle. \qquad (4)$$

There are three well-known kernels, i.e. of linear, polynomial and Radial Basis Function (RBF) type. In this work, the RBF kernel is used.

2) LS-SVM Regression

Similar to the SVM regression, the dual space formulation of the LS-SVM writes:

$$M\left(\mathbf{x}\right) \approx M_{LS-SVM}\left(\mathbf{x}\right) = \sum_{i=1}^{L} \beta_i K\left(\mathbf{x}_i, \mathbf{x}\right) + b \qquad (5)$$

Where $\beta_i \in \mathbb{R}$ are the regression coefficients, $K(\cdot,\cdot)$: $\mathbb{R}^{d\times d} \rightarrow \mathbb{R}$ is the kernel function and $b \in \mathbb{R}$ is the bias term. The LS-SVM regression estimates the coefficients β_i and the bias term b by minimizing the squared error between the model prediction and the training output and at the same time by maximizing the model flatness. Different from the SVM regression, the parameters β_i and b for the LS-SVM regression can be estimated using the solution of a "simple" linear system. In this work, the RBF kernel will be used for the LS-SVM regression. The LS-SVM regression is already implemented in MATLAB within LS-SVM Lab Toolbox [10].

3) Gaussian Process Regression

GPR approach calculates the probability distribution over all acceptable functions that fit the data. In GPR, a Gaussian process prior is assumed, which can be specified using a mean function, $\mu(\mathbf{x})$, and covariance function, $K(\mathbf{x}, \mathbf{x}')$ as follows,

$$M_{GPR}(x) \sim GP(\mu(\mathbf{x}), K(\mathbf{x}, \mathbf{x}')) \qquad (6)$$

For a given set of training samples D, the posterior distribution $p(y_*|\mathbf{x}_*, D)$ allows to estimate the output variable $y(\mathbf{x}_*)$ for any configuration $\mathbf{x}_*$ of the input parameters. The posterior distribution provides as output a normal distribution:

$$p(y_*|\mathbf{x}_*, D) \sim \frac{1}{\sigma_*\sqrt{2\pi}} exp\left(-\frac{(y(\mathbf{x}_*) - \mu_0)}{\sigma_*}\right)^2 \qquad (7)$$

Where

$$\mu_* = K_*^T K^{-1} y \qquad (8)$$

$$\sigma_*^2 = K_{**} - K_*^T K^{-1} K_* \qquad (9)$$

And μ_* and σ_*^2 are the posterior mean and variance, respectively. Also, K is the covariance matrix evaluated on the training input and $K_* = K(\mathbf{x}_i, \mathbf{x}_*)$ for $i = 1, \ldots, L$, $K_{**} = K(\mathbf{x}_*, \mathbf{x}_*)$. Under some assumptions, a model based on the GPR can provide a reliable prediction for the actual value of the output. Also, the GPR approach is able to deal with noisy data [4].

4) Random Forest Regression

Random forest algorithms are frequently used in machine learning applications. The main advantage of RFs is improving the computing efficiency and prediction. The RF is a supervised learning algorithm that consists of many decision trees and nodes. Also, it uses the concept of multiple random trees being generated with training dataset. A decision tree consists of a set of nodes connected each other nodes through the branches, thus creating graphs oriented in descending direction that starts from a single root node and ends in a series of leaf nodes. It should be noted that in random forest regression, an adaptive algorithm can be useful for determining the unknown weights [3].

In literature [11], it is shown that LS-SVM, SVM and GPR provide an accurate model and are robust against the noise. Also, all four algorithms can be trained with a limited set of training samples. The SVM, LS-SVM and RF can handle a large number of input variables and have large variability but only GPR provides reliable information on its prediction accuracy.

III. APPLICATION EXAMPLE

This section presents the performance of the four above-mentioned algorithms for the characteristic impedance calculation of a microstrip structure. The dataset in [9] is considered. It consists of 20,440 samples obtained via a set of full-wave simulations with Sonnet software in a bandwidth from 1 GHz to 10 GHz, in which the substrate height H, the relative permittivity ε_r and the trace width W of the microstrip are varying uniformly such as: 0.25 mm $\leq H \leq$ 3.175 mm, 1 $\leq \varepsilon_r \leq$ 7, 0.2 mm $\leq W \leq$ 5. The above dataset has been split into the training and test set.

So, for each frequency, a subset of L training samples is randomly selected. Also, to investigate the robustness of the introduced algorithms to noisy data, the training samples are corrupted by a Gaussian noise as follows:

$$y_{i,\,noisy}\left(\mathbf{x}_i\right) = y_i\left(\mathbf{x}_i\right) \times \left(1 + \zeta_n\right) \qquad (10)$$

Where $\zeta_n \sim N(0, \sigma_n^2)$ is a Gaussian variable with $\sigma_n = 0.6$. Figures (1) to (3) show the scatter plots providing the correlation between the prediction of the proposed four algorithms with respect to the actual values of the characteristic impedance in the presence and absence of noise for different value of L at frequency 2GHz by considering 5,700 test samples.

As expected, by increasing the the number of training samples L, the deviation of the model prediction with respect to the ideal case (black dashed line) decreases.

The plots clearly highlight that among the considered methods, GPR and LS-SVM have shown the good performance for the noiseless case, but the SVM regression seems to perform better with noisy samples. The above reasoning is confirmed by the results collected in Table I, which shows the mean square error computed on 5,700 test samples.

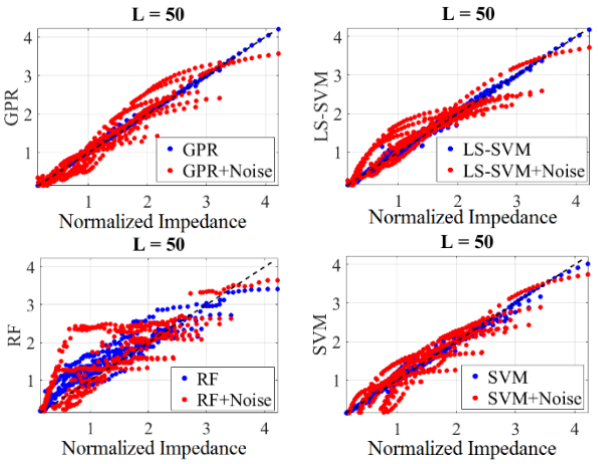

Fig.1. Scatter plots obtained by the four algorithms with L=50.

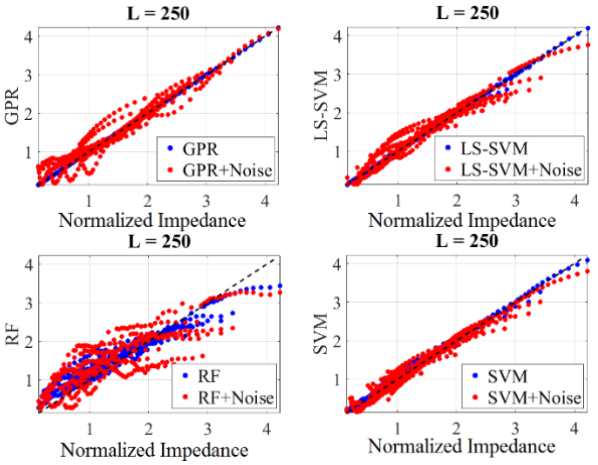

Fig.2. Scatter plots obtained by the four algorithms with L=250

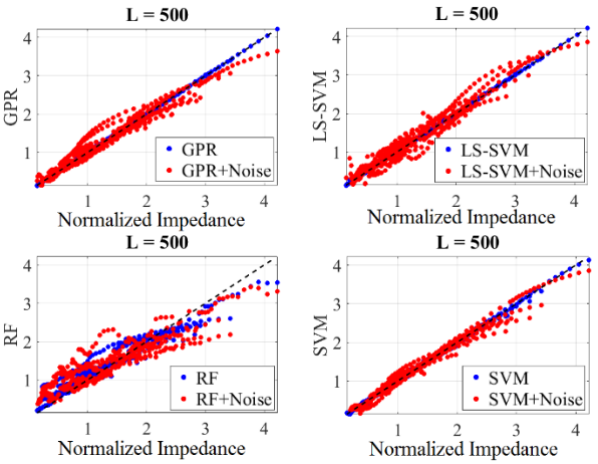

Fig.3. Scatter plots obtained by the four algorithms with L=500

Table I: the mean square error of the four metamodels.

Model	*L*=50		*L*=250		*L*=500	
	No Noise	Noise added	No Noise	Noise added	No Noise	Noise added
GPR	0.001	0.066	7.28e-05	0.046	4.08e-05	0.032
LS-SVM	0.003	0.08	6.45e-04	0.033	1.7e-4	0.038
RF	0.118	0.176	0.069	0.197	0.058	0.138
SVM	0.007	0.093	0.003	0.019	0.001	0.015

IV. Conclusion

In this paper, four ML regression techniques have been applied for the prediction of characteristic impedance of a microstrip line as a function of three parameters, i.e., substrate dielectric constant, height and strip width. The dataset is obtained from a set of simulations carried out with Sonnet software [9]. The training data are used to create the model and the test data are considered to qualify the established model. Also, the robustness of four regression techniques to noisy training samples are considered. The performances of the proposed methods are compared with the desired data. It is shown that the GPR and LS-SVM have good performance for the noiseless case, whilst the SVM turns out to be more robust with respect to noise. Such methods are suitable for electromagnetic problems where there is no explicit relationship between input and output parameters of the system.

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