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Transmission line impulse response modelling using machine learning techniques

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ABSTRACT

Conventional methods of circuit simulation such as full-wave electromagnetic field solvers can be very slow. Machine learning is an emerging technology in modelling, simulation, optimization, and design that present attractive alternatives to the conventional methodologies because they can be trained with a small amount of data, and then used to perform fast circuit predictions within the same design space. In this paper, we present applications of machine learning techniques for the modelling of transmission lines from their impulse reponses. The standard multilayer perceptron (MLP) neural network and the gaussian process (GP) regression techniques are demonstrated, and both models are successfully implemented to model the impulse responses of transmission lines with great accuracies. We show that the GP outperforms the MLP in terms of prediction accuracies and that the GP is more data efficient than the MLP. This is beneficial considering that each training sample is expensive, making the GP a good candidate for the task, compared to the more popular MLP.

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1. INTRODUCTION

Advanced modelling and simulation techniques are crucial in analysing the electrical performances of complex electronic packages and other interconnections in order to achieve a first-pass design success [1]. However, computer-aided design (CAD) tools of high-speed circuit components typically require the development of specific codes or algorithms for the simulation process. These conventional ways to simulate circuits are computationally expensive and time consuming, which slows down the design and development process, in addition to requiring specific knowledge and engineering know-hows to run and produce the required results. On top of that, the simulation of the design has to be repeated whenever there are any changes to the simulation parameters, which further adds to the development time.

Machine learning algorithms are efficient alternatives to conventional methods such as full-wave electromagnetic (EM) simulators, which are very accurate but computationally very slow. While analytical methods and empirical models are much faster, they are not easy to obtain for new devices, and their accuracy and range could be limited. In the past two decades, machine learning models have been used in the modelling of various radio frequency (RF) and microwave structures such as antennas and microwave filters [2]-[3]. A recent review of machine learning techniques on RF and microwave circuit modelling can be found in [4]. The working principle of machine learning models is that they can be trained to learn the behaviour of individual circuit components, and then the trained model can be used for high-level design. Normally, the machine learning models are much faster during the predicting than training. Thus, the circuit designers will often spend a considerable amount of time to train the machine learning models. However, machine learning models often require a large amount of data to be properly trained, and the generation of these data can be very time consuming, especially if they are generated using full-wave EM simulators, physics-based models, or measurements [5]. Thus, it is beneficial to have machine learning models which can be easily and quickly trained with a limited amount of data.

The artificial neural network (ANN) is one of the most popular machine learning methods for circuit modelling. Besides being used for various microwave and RF circuit modelling [6]-[7], the ANN has also been used for various signal integrity modelling tasks involving high-speed channels [8], [9]. These include modelling of crosstalk [10], eye diagram [11]-[12], and transient responses [13], [14]. The Gaussian process regression (GP) model is another alternative to the ANN. Similar to the ANN, the GP has also been used for the modelling of various microwave structures such as the microwave filter [15], microwave antenna [16], and microwave amplifier [17]. Inspired by the success in the implementations of ANN and GP in the field of circuit modelling, this paper aims to demonstrate the use of GP and multilayer perceptron (MLP) neural networks for the modelling of transmission lines based on their impulse responses. Section 1 of this paper describes the introduction and motivation behind this work. Section 2 describes the fundamentals of MLP and GP. Section 3 describes the time domain modelling of trainsmission lines, and the motivation behind the utilization of the impulse response. The training process of the machine learning models are described in section 4, and the results and discussions are presented in section 5. Finally, conclusions and future works are proffered in section 6.

2. MULTILAYER PERCEPTRON AND GAUSSIAN PROCESS

The MLP is a popular neural network structure consisting of multiple connected network layers [18]. Figure 1 shows an MLP neural network with L layers. It consists of an input layer, an output layer, and one or more hidden layers, where each layer has N_i neurons. The MLP receives the inputs, $x = \{x_1, x_2, x_3, \ldots, x_{N_1}\}$ and generate the outputs, $y = \{y_1, y_2, y_3, \ldots, y_{N_L}\}$. For many modelling problems, a simple MLP neural network consisting of a single hidden layer is sufficient, thanks to the basic characteristics of neural networks, which include inherent parallelism, fault tolerance, and learning and self-adaptability, which allows them to model even highly non-linear functions [19]. Sometimes, two hidden layers will be used for more complicated problems. Multiple papers have been published on MLP neural network applications, for example on fingerprint image region of interest segmentation [20], high-electron-mobility transistor (HEMT) modelling [21], and the modelling of terminal electrical noise in semiconductor lasers [22]. The basic feature of an ANN is the capability to learn the patterns of the input samples to predict the system behaviour. Once the network has learnt the input-output relationships, it can then produce outputs for other inputs, even those that were not encountered during training. In machine learning terms, this is known as generalization [23]. In the context of ANN, the term learning refers to the method of varying the weights of the connecting links between the neurons of the network to match to the desired output. Further background on the MLP can be found in [24].

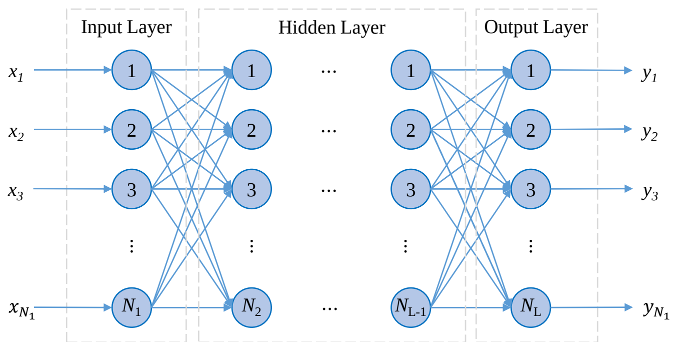

Figure 1. The MLP structure

The GP is a stochastic modelling methodology that is often used for modelling spatially correlated measurements. GP can be succinctly described by

$$f(\mathbf{x}) \sim GP\left(\mu(\mathbf{x}), k\left(\mathbf{x}, \mathbf{x}'\right)\right) \tag{1}$$

where the function is completely defined by its mean function $\mu(\mathbf{x})$ and covariance function $k\left(\mathbf{x}, \mathbf{x}'\right)$ [25]. In other words, GP can be viewed as a generalization of the multivariate Gaussian probability distribution where the evaluations for the inputs $\mathbf{x}_1, \ldots, \mathbf{x}_N$ are normally distributed as

$$\left[\begin{array}{c} f\left(\mathbf{x}_1\right) \\ \vdots \\ f\left(\mathbf{x}_N\right) \end{array}\right] \sim \mathcal{N}(\mu, \mathrm{K}) \tag{2}$$

in which

$$\mu=\left[\begin{array}{c} \mu\left(\mathbf{x}_1\right) \\ \vdots \\ \mu\left(\mathbf{x}_N\right) \end{array}\right] \tag{3}$$

and

$$k=\left[\begin{array}{ccc} k\left(\mathbf{x}_1, \mathbf{x}_1\right) & \cdots & k\left(\mathbf{x}_1, \mathbf{x}_N\right) \\ \vdots & & \vdots \\ k\left(\mathbf{x}_N, \mathbf{x}_1\right) & \cdots & k\left(\mathbf{x}_N, \mathbf{x}_N\right) \end{array}\right] \tag{4}$$

The covariance function and mean function play a significant role in a GP-based model. On the other hand, the structure of an MLP model will influence the performance of the model. Several procedure have been implemented in this project to increase the accuracy of the models. Optimization of hyperparameters are done to cope with the real-world non-ideal problem. The hyperparameters for the covariance function and mean function in the GP models are also optimized. Furthermore, the structure or hidden units of the MLP models are investigated to ensure that the best performing model is selected.

3. TIME DOMAIN IMPULSE RESPONSE MODELLING OF TRANSMISSION LINES

Transmission lines are interconnects that relay signals from the transmitters to the receivers on high-speed electronic circuits. They are formed by a combination of conductors and dielectric materials to guide a signal along the desired path. Generally, the characteristic impedance, or natural impedance Z is the main parameter of a transmission line as it defines the behaviour of the line. The characteristic impedance is calculated as:

$$Z=\sqrt{\frac{R+j\omega L}{G+j\omega C}} \tag{5}$$

where R, L, G, and C are the per unit length series resistance (Ω/m), series inductance (H/m), shunt conductance (Ω^{-1}/m), and shunt capacitance (F/m) respectively. The physical dimensions of the printed circuit board traces or the transmission lines play a significant role in the effects of the characteristic impedance as they alter the values of the electrical parameters. For example, the capacitance, C, for a parallel plate structure is calculated as:

$$C=\frac{\varepsilon A}{d} \tag{6}$$

where d is the substrate height, A is the area of the trace, and ε is the dielectric constant of the surrounding material.

Studying the behaviour of an electronic circuit system is essential before training a machine learning model to learn the behaviour of the system. The Gaussian impulse response is the output voltage generated by the electronic circuit system with a Gaussian impulse signal as the input. The Gaussian signal in the time domain is selected as the input since the Gaussian transient response represents the behaviour of the electronic circuit system under various frequencies. It can be shown that the Fourier transform of a Gaussian signal is another Gaussian signal [26], where the Fourier transform is a well known tool that can be used to decompose a function or signal into its constituent frequencies. Thus, it is possible to predict the behaviour of the circuit over those frequencies given its Gaussian impulse response.

In this work, circuit modelling of transmission lines are performed using their Gaussian impulse responses. Firstly, frequency domain simulations are performed on transmission lines with different design parameters to extract their S-parameters. Then, circuit simulations using these S-parameters under a Gaussian excitation are performed to extract the impulse responses of the transmission lines. The voltage source, $S(t)$ that acts as the input is defined as:

$$S(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2} \tag{7}$$

where μ represents the mean and σ represents the standard deviation that defines the bandwidth of the Gaussian signal. The circuit simulation setup is shown in Figure 2. The design parameters of the transmission line considered in this work are: line length, l from 1000 mils to 3700 mils and line width, w from 50 mils to 110 mil. Figure 3 shows the impulse responses of two randomly selected transmission lines cases, where Figure 3(a) shows test case 1 and Figure 3(b) shows test case 2.

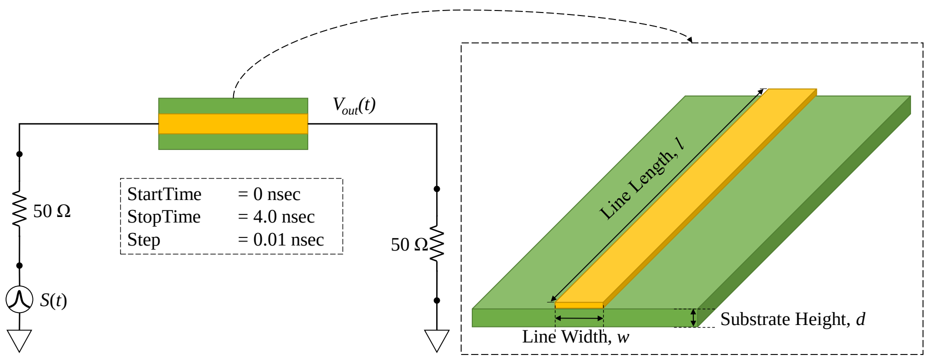

Figure 2. Circuit simulation setup and transmission line parameters

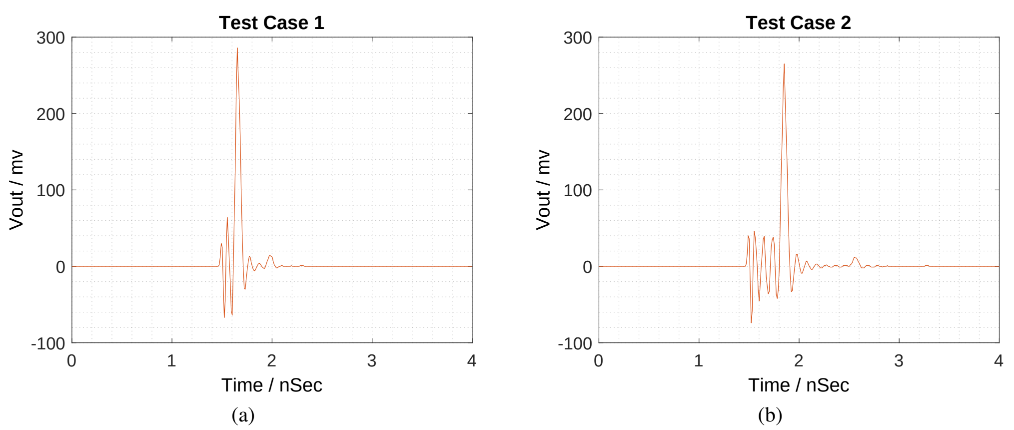

Figure 3. The impulse response, $V_{out}(t)$ of (a) test case one and (b) test case two

4. TRAINING OF MACHINE LEARNING MODELS

The training process of a MLP model involves searching for a set of weights and biases that results in good generalization. The number of neurons and their activation functions are also optimized. In this work, the training is done using the Levenberg-Marquardt backpropagation algorithm [27]. MLP models consisting of one hidden layer and varying numbers of hidden neurons are trained. Grid search is performed for the purpose of hyperparameters optimization, which involves sweeping the number of hidden neurons from 10 to 100 with a step of 10, and each configuration is trained 10 times to minimize the random nature of training. The performances of the models are ranked based on their coefficient of determination, or R-squared values.

In contrast, for a set of training data, a GP model produces a distribution of multiple possible functions with an optimized weight vector, and not just one single function. GP models are specified by their mean and covariance functions, but these functions cannot be fully specified a priori. Instead, they form a set of hyper-parameters, that is, parameters which have to be determined during training. In this work, first, the declaration and initialization of the covariance function, mean function, and their hyperparameters are done. Then, the hyperparameters are optimized with the aid of the Gaussian processes for machine learning (GPML) toolbox [28]. The optimization is done by minimizing the negative log marginal likelihood together with the partial derivatives with respect to the hyperparameters. Finally, the optimized hyperparameters are implemented in training the GP model as well as predicting the unseen inputs.

5. RESULTS AND DISCUSSION

In many circuit modelling applications, the generation of the training data can be a very computationally expensive process, as each data requires an intricate simulation setup and solution process. Thus, it is highly beneficial to have models which are able to function based on a small or limited data sample. In this work, the data of 70 transmission line designs are utilized and the data is divided into subsets for training, validation, and testing with a ratio of 50:10:10. The training results of the MLP models are tabulated in Table 1. By comparing the R-squared values, the model with 50 hidden neurons is selected as the best performing model since the model has the greatest R-squared values.

Table 1. Training results of the MLP models

No. of neurons	Training R^2	Validation R^2	Testing R^2	Training time (s)
10	0.9276	0.9286	0.9115	9.001
20	0.9347	0.9154	0.9399	25.605
30	0.9265	0.9274	0.9288	11.498
40	0.9255	0.9379	0.9346	23.713
50	0.9408	0.9540	0.9455	29.734
60	0.9307	0.9384	0.9371	72.201
70	0.9367	0.9196	0.9227	39.845
80	0.9320	0.9278	0.9366	50.927
90	0.9326	0.9352	0.9142	75.359
100	0.9277	0.9352	0.9289	82.341

Table 2 compares the performances of the MLP and GP models. The results show that the GP model outperforms the MLP model in both training and testing accuracies. Besides that, the results also show that the training of the MLP model is more arduous than the GP model. However, the MLP model can predict much faster than the GP model. The GP model shows a higher level of accuracy than the MLP model when both of them are trained on small amount of samples, which means that the GP is a very data efficient model. However, the slow prediction speed of GP can be a limitation when modelling large amount of designs. Other than that, further increasing the amount of training samples can also slow down the prediction speed of the GP model even more, whereas the prediction speed of the MLP is not affected by the size of training samples as long as the model complexity remains the same. Nevertheless, the training time of the MLP will increase with the increase in the size of the training dataset. Figure 4 shows the comparison of the actual impulse responses and the MLP predictions, where Figure 4(a) shows the result for test case one and Figure 4(b) shows the result for test case two. Figure 5 shows the comparison of the actual impulse responses and the GP predictions, where Figure 5(a) shows the result for test case one and Figure 5(b) shows the result for test case two.

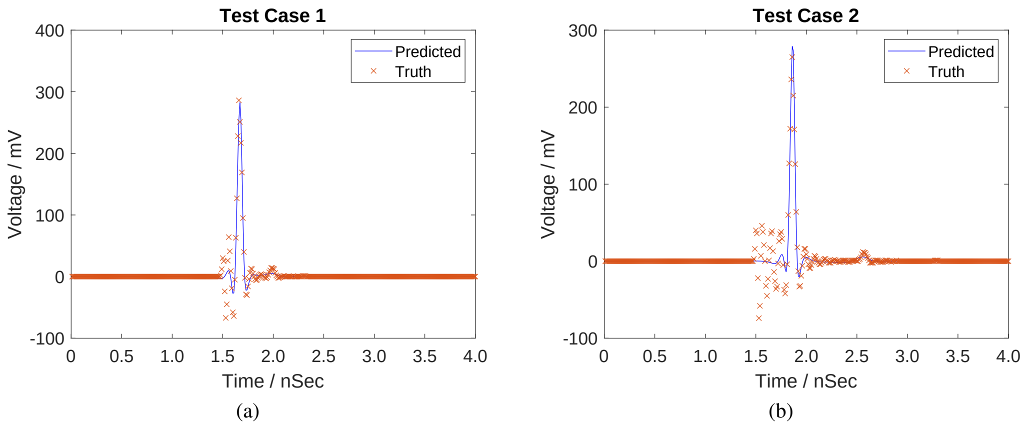

Figure 4. The impulse response, $V_{out}(t)$ simulated by the circuit simulator versus MLP predictions of the (a) test case one and (b) test case two

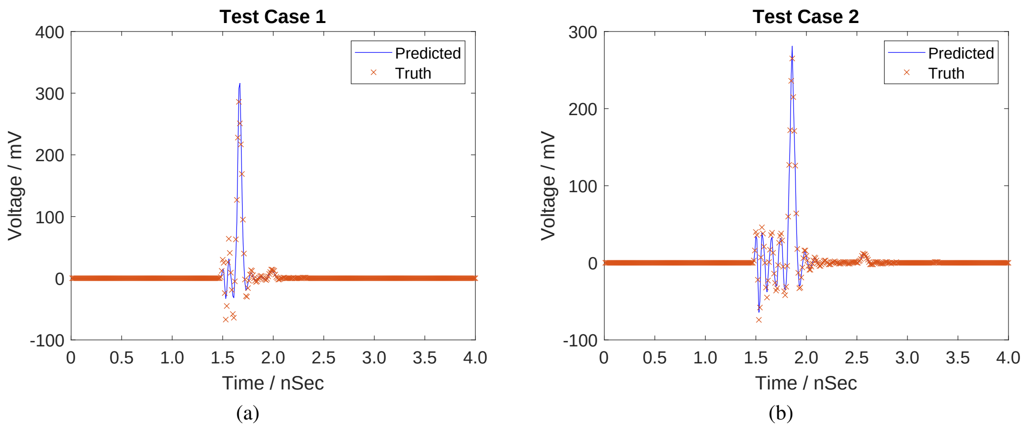

Figure 5. The impulse response, $V_{out}(t)$ simulated by the circuit simulator versus GP predictions of the (a) test case one and (b) test case two

Table 2. Comparisons between the MLP and GP models

	Model	
Performance metric	MLP	GP
Training MSE	54.29	2.43×10^{-3}
Testing MSE	83.09	22.21
Average training time (s)	29.7	6.9
Average prediction time (s)	2.18×10^{-2}	1.48

6. CONCLUSION

In conclusion, both the MLP and GP models show promising results on the time domain impulse response modelling of transmission lines. On one hand, the GP model shows better performance (lower training and testing errors) when trained on a small dataset, while the MLP model has a faster prediction speed. Despite that, we believe that the high data efficiency of the GP model far outweighs its shortcomings, especially when each training sample is very expensive to produce. As a future work, the size of the design space can be expanded to include increasing amounts and ranges of design parameters in order to better model more complicated problems. In this case, the data efficiency of the models will play an important role in optimizing the modelling process.

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