AI-based Hybrid Approach (RL/GA) used for Calculating the Characteristic Parameters of a Single Surface Microstrip Transmission Line

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***Abstract*— This article presents an approach for a hybrid AI method (for predicting the characteristic parameters of line networks on PCBs using a simple example (single surface microstrip structure -outer layer). This article is part of the current developments in the field of Physically Based AI Methods for EDA Applications. The contribution presented here must be understood as a proof of concept and serves to better understand the application of a hybrid algorithm (ML-Assisted GA: DDRL + GA) for the purpose of shape optimization in the solution of physics-based problems with the application to a simple problem (field problem for Q-TEM structures; single surface microstrip). To determine the characteristic parameters for the Q-TEM case, the shape of potential curve describing the solution of the corresponding field problem is determined using Thomson's theorem (energy minimum of the microstrip arrangement under consideration).**

Keywords*— Physical-driven scientific computing; physically based AI methods; machine learning; predictive modelling; single surface microstrip; degenerate deep reinforcement learning; genetic algorithms; signal integrity; computational electromagnetics; EDA applications.

I. Introduction

To calculate the characteristic parameters of transmission lines on a PCB, the structure to be considered must first be physically described and the necessary physical knowledge regarding AI modelling must be prepared. The following planar structure according to Figure 1 is used as a model.

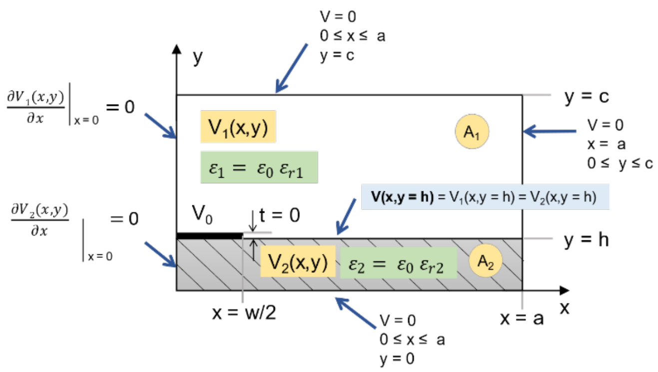


Fig. 1. Physical model for a plane symmetrical single surface microstrip structure

First, a boundary value problem must be defined in which the electric potential (Q-TEM) on the conductive surface and the conductive boundary of the structure is predetermined, but unknown on the charge-free surface.

The solution of the Laplace equation associated with the Q-TEM case addressed here is described by a Fourier series approach [1]. The unknown series coefficients are determined using first-order spline functions to describe the potential at the boundary layer between two dielectrics and to minimize the electrostatic energy W'e in the region under consideration [2]. Thomson's theorem [3] is used for this purpose.

The new approach for the implementation of deep reinforcement learning (degenerate deep reinforcement learning (single-step DRL)) presented in [4] is used here to find the required shape of the potential function respectively the electrostatic energy W'e and its corresponding characteristic transmission line parameters.

DRL helps achieve a near-global solution initially, which is further optimized using a Genetic Algorithm (GA) [5]. A bezier curve-based shape drawing technique (calculation of a near-global optimum potential curve) is used for the DRL approach (scaled reward system).

The metric behaviour (critical/actor loss/entropy coefficient/reward) of the implemented DDRL as a function of training time will be discussed. The physical results obtained (potential curve (shape) + energy + surface charge density and the resulting transmission line parameters) are compared with results from the literature [5] [10].

II. Physical Modelling of the Problem (Physical Preconditions for Solving the given Field Problem)

The following system-describing equation (Laplace equation) can then be solved for the single microstrip arrangement shown in Figure 1:

$$\triangle V\,(x,\,y) = 0. \tag{1}$$

To calculate the required line parameters Z_D and ϵ_{eff}, the length-related capacity parameters (plane problem) C'_D (and C'_L must be determined; two separate calculation steps are therefore necessary. The following equations apply:

$$C'_{D;L} = \frac{2\,W'_{e|D;L}}{V_0^2}\;; \tag{2a}$$

$$\epsilon_{\rm eff} = \frac{C'_D}{C'_L}\;,\quad v_{\rm ph} = \frac{c_0}{\sqrt{\epsilon_{\rm eff}}}\;; \tag{2b}$$

$$Z'_D = \frac{1}{c_0\sqrt{C'_D C'_L}} \;, \quad Z'_L = \frac{1}{c_0 C'_L} \qquad (2c)$$

c_0: Vacuum speed of light.

The required capacitances can be determined by calculating the electrical energy W‘e in the areas A1 and A2; at this point, it is time to once again recall the requirements of the approach chosen for Q-TEM:

$$C'_D = \frac{2W'_{e|D}}{V_0^2} \;, \quad C'_L = \frac{2W'_{e|L}}{V_0^2} \;. \qquad (3)$$

The required energy W'e|1 and W'e|2 of the electric field for the areas A1 and A2 can be calculated with the help of the potential distributions V1(x,y) and V2(x,y). These potential distributions are determined by solving the Laplace equation using Bernoulli's product approach. For the potential shape V (x, y = h) then applies [1], [11]:

$$V(x, y = h) = \sum_{n=0}^{\infty} v_n \cos\left((2n+1)\frac{\pi}{2}\frac{x}{a}\right) \;. \qquad (4)$$

III. Shape Modelling

Since the potential distribution is symmetrical across the microstrip, we can look at one-half for further analysis. Typically, the solution of the field problem described above leads to the potential shape given in Figure 2.

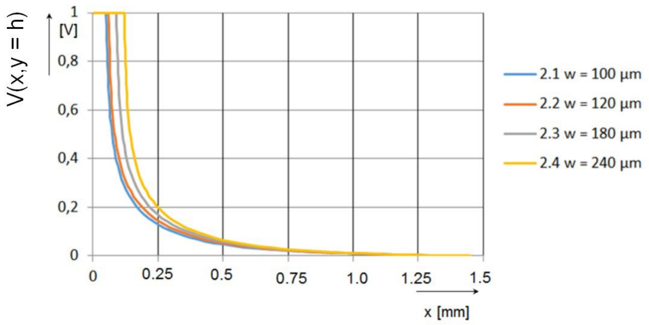


Fig. 2. Potential shape for different single surface microstrip widths

It is now time to determine the unknown v_n from equation (4). To do this, the potential distribution V (x, y = h) will be approximated by 1st order spline functions.

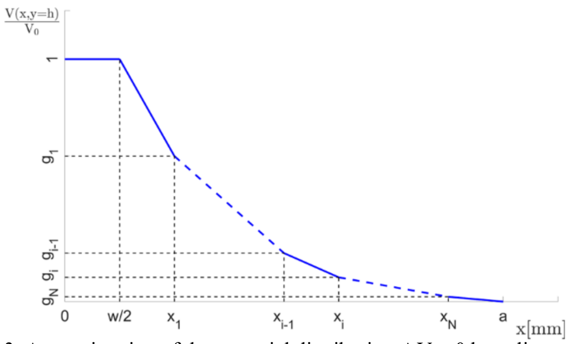


Fig. 3. Approximation of the potential distribution $\triangle V = 0$ by spline functions of the 1st order (symmetric problem)

The required potential coefficients v_n can now be expressed by using the orthogonal nature of the trigonometric functions in the form of 1st order spline functions.

$$v_n = \frac{2}{a}V_0\left[\frac{1}{\left[(2n+1)\frac{\pi}{2a}\right]^2}\right]\cdot\left[\frac{g_1-1}{x_1^G-d}\left[\cos\left((2n+1)\frac{\pi}{2a}x_1^G\right) -\cos\left((2n+1)\frac{\pi}{2a}\frac{w}{2}\right)\right] + \sum_{i=2}^{N}\frac{g_i-g_{i-1}}{x_i^G-x_{i-1}^G}\left[\cos\left((2n+1)\frac{\pi}{2a}x_i^G\right) -\cos\left((2n+1)\frac{\pi}{2a}x_{i-1}^G\right)\right] + \frac{g_N}{a-x_N^G}\cos\left((2n+1)\frac{\pi}{2a}x_N^G\right)\right]. \quad (5)$$

The energy W'e of the electric field can then similarly be determined by using the orthogonal nature of the trigonometric functions as a function of the potential coefficients v_n.

$$W'_e = \frac{\varepsilon_1}{4}\left[\sum_{n=0}^{\infty} v_n^2\,[(2n+1)\,\pi]\,\frac{\cosh\left((2n+1)\frac{\pi}{2a}(c-h)\right)}{\sinh\left((2n+1)\frac{\pi}{2a}(c-h)\right)}\right] + \frac{\varepsilon_2}{4}\left[\sum_{n=0}^{\infty} v_n^2\,[(2n+1)\,\pi]\,\frac{\cosh\left((2n+1)\frac{\pi}{2a}h\right)}{\sinh\left((2n+1)\frac{\pi}{2a}h\right)}\right]. \qquad (6)$$

IV. Development of a Single Stage DDRL Model

In order to find the optimal shape of the potential distribution for a microstrip configuration as shown in Figure 1, an optimization problem can be formulated in such a way that energy W’e of the electric field must be minimized in the region under consideration (see Equation 6; [2]).

In this paper, as mentioned above, the approach discussed in [3] and [4] is used to implement a degenerate deep reinforcement learning (single-step DRL) to solve the potential problem given here (Figure 4).

Figure 4: Degenerate Deep Reinforcement Learning Framework (single-step DRL); the run-through for an episode is shown

The three basic components must be defined for each DRL problem: Observation Space, Action Space, and Reward Scheme (Figure 5).

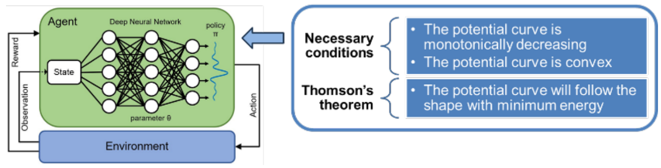


Fig. 5. Deep reinforcement learning concept

The model is trained with a SAC (Soft Actor Critic [7]) agent for TC 2.1 (D/L) environments separately. SAC presents an algorithm that optimizes a stochastic policy through off-policy methods, effectively bridging the gap between stochastic policy optimisation and DDPG-style approaches.

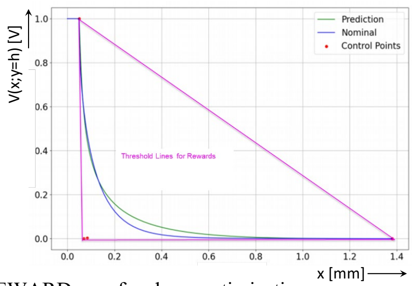


Fig. 6. Allowed REWARD area for shape optimization

A central feature of SAC lies in entropy regularization. Therefore dynamic entropy coefficients are deployed to boost exploration. The admissible REWARD area for optimizing a potential shape is shown in Figure 7.

A. First Training Results TC2.1 L

Without limiting the generality, the training results achieved for test case 2.1 (w/2 = 50 µm; a = 1.38 mm; h = 0.1382 mm; c = 2.76 mm; ε_{r1} = 1.0; ε_{r2} = 1.0). The metric behaviour of critic, actor loss, entropy and reward coefficient is shown in Figure 7 and 8.

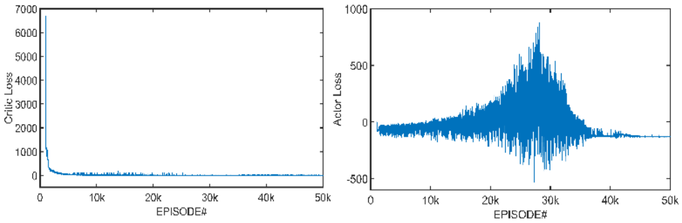


Fig. 7. Metric behaviour critic + actor loss as a function of training steps

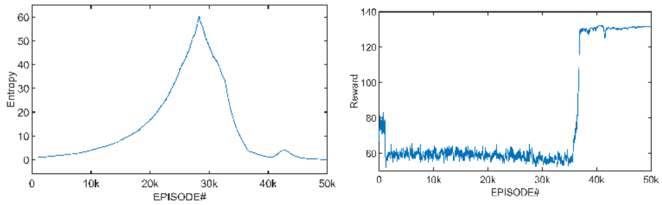


Fig. 8: Metric behaviour entropy coefficient + reward as a function of training steps

It can be observed that convergence can be achieved after about 40K training episodes. The computation time for training this model is ~ 12 minutes (50 K). Once the trained model is available, the prediction time for each new microstrip configuration is in the range of 3 and 8 ms. A typical potential shape as a dependency of the training episodes for is shown below in normalized form (Figure 9).

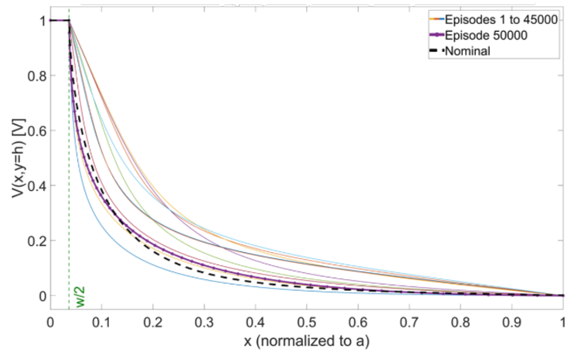


Fig. 9. Training results Soft Actor-Critic (SAC) agent - Potential curve for Test Case 2.1 in normalized representation (episodes# as parameter)

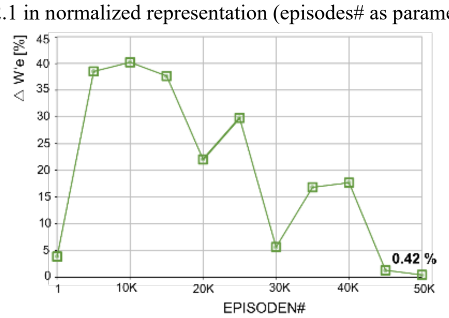


Fig. 10. Relative error of the electrostatic energy △ W'e for TestCase 2.1 parameters (reference nominal value obtained from [11])

Compared to the nominal value [5] of the electromagnetic energy (1.155E-11 VAs), the achieved training value (1.160E-11 VAs) deviates by only 0.41 % (Figure 10).

Nevertheless, it must generally be assumed that the potential curve (and thus the searched electromagnetic energy of the arrangement) could not always be optimally predicted for very narrow strip widths (h ≫ w). This must be taken into account for further considerations on the use of training DDRL models (deployment). Therefore, based on the results predicted by the DDRL model developed here, a GA algorithm [4] is used in each case to improve the search for the appropriate energy minimum (ML assisted GA). The GA code already used in [8] is used for this purpose; see Figure 12.

V. Minimizing The Influence Of The Metallic Enclosure

The distance between the transmission line and the metallic enclosures must be sufficiently large to rule out any influence on the field distribution compared to the open microstrip arrangement. Detailed energy predictions show that there is a greater sensitivity with regard to the parameter a [11].

The following Figure 11 shows the progression of the energy W'e as a function of the parameter a as a result of a first (1 ≤ a ≤ 8 mm) and a second run (1 ≤ a ≤ 2 mm) for the arrangement according to Figure 1.

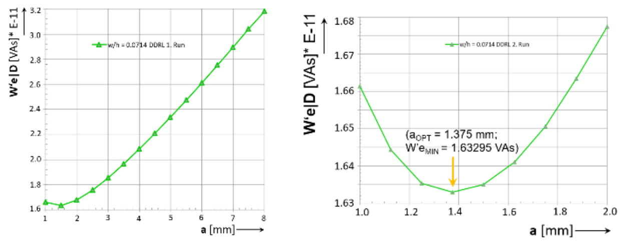


Fig. 11. PCB layer stack h =140 µm/ε_{r2} = 4.0/w = 10 µm

In order to minimize the influence of the parameter a, a special algorithm was developed to determine an optimal a value based on the existing DDRL training environment (Figure 12).

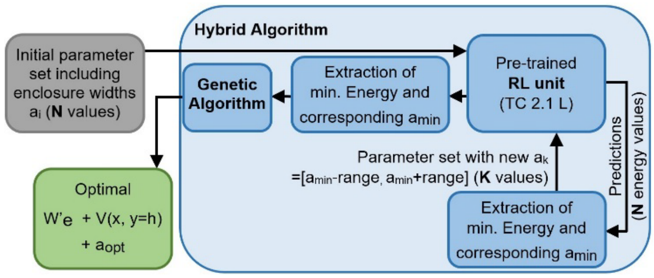
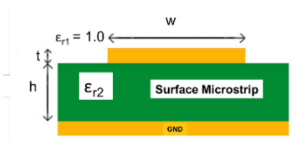


Fig. 12. ML assisted GA process (hybrid algorithm)

VI. Application Example – Prediction Impedance And Efective Dielectric Consatant

CASE#	w [mm]	w/h
LS1L5-1 LS1D5-1	0.01	0.0714
LS1L25-1 LS1D25-1	0.05	0,357
LS1L50-1 LS1D50-1	0.1	0,714
LS1L100-1 LS1D100-1	0.2	1,43
LS1L250-1 LS1D250-1	0.5	3,57
LS1L500-1 LS1D500-1	1.0	7,14



CASE#	ε_{r1}	ε_{r2}
TC2.1 L/D	1.0	12.9
LS1 5 – 500 L/D	1.0	4.0

Fig. 13. Application example parameter set LS1 5 – 500 PCB top layer (data source MultiPCB)

Note: To correct the approach presented here for a strip thickness not equal to zero ($t > 0$), a method described by [10] can be used without any problems. Equations are given there that enable the calculation of a strip width w' equivalent to $t \neq 0$. This allows the field problem to be returned to the energy calculation approach described above.

The following Figure 14 show the characteristic impedances Z_L and Z_D and the effective dielectric constant $\varepsilon_{eff|D}$ respectively $W'e_{L|D}$ as a function of w/h for the prediction using DDRL (predictions model TC 2.1 L) and the subsequent GA optimization.

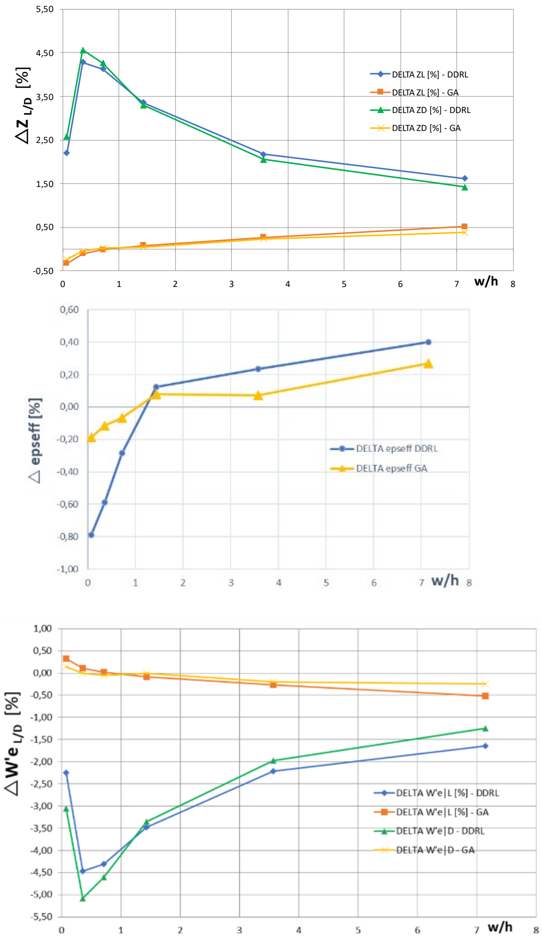


Fig. 14. Relative deviation of Z_L and Z_D respectively $\varepsilon_{eff|D}$ and $W'e_{L|D}$ as a result of DDRL prediction and GA optimization (reference values from [10])

The maximum deviation (after GA optimization) is 0.5 % for Z_L and 0.4 % for Z_D and 0.3 % for $\varepsilon_{eff|D}$ compared to the reference value according to [10]. A comparison of the predicted and subsequently optimized energy values shows greater deviations from the reference values for small strip widths [10] than for wider strips. However, this is also simple to explain, as the field inhomogeneity is significantly lower for wider strips than for smaller strips. This shows that the trained DDRL model (here used model TC2.1 L) correctly reproduces the physical conditions of the underlying arrangement within the expected error margins.

VII. Conclusions

The DDRL approach developed here forms a model approach for data-efficient shape approximators (Physically Based AI Methods; AI-based Hybrid Approach (RL/GA)) with which - as shown - field problems (calculation of the characteristic impedance and the associated effective dielectric constant (surface microstrip)) can be solved in a wide parameter space.

The results obtained show that almost global solutions can be achieved for test cases that deviate slightly from the training case.

In order to extend the understanding of the use of DRL methods, the model approach developed here is to be expanded into a model family for solving more complex field problems such as edge-coupled surface microstrip lines and embedded striplines. It should also be considered whether it is then possible to include conductor losses (dielectric/surface roughness/copper losses) (conductor surface roughness effect) in the model family.

With the extensive knowledge/experience then available, it will be possible to use these AI methods for the actual goal of predicting signal characteristics for SI design issues. If it is possible to train a DDRL model in such a way that a prediction of the required characteristic transmission line parameters in a wide parameter range is possible, a new DDRL model family for SI applications will be created. With a subsequent GA optimization, several design alternatives can then be made available to the PCB-SI engineer very quickly (run time reduction).

Acknowledgment

This work is funded as part of the research project KI4BoardNet in the funding programme MANNHEIM (BMBF) (Grant numbers 16ME0779/TUDO - 16ME0777/IDMT). The responsibility for this publication is held by the authors only.

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