Estimating Per-Unit-Length Resistance Parameter in Emerging Copper-Graphene Hybrid Interconnects via Prior Knowledge based Accelerated Neural Networks

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Abstract — **In this paper, an artificial neural network (ANN) is developed to model how the geometrical parameters of hybrid copper-graphene interconnects affect the per-unit-length resistance values. The proposed ANN is intelligently trained using large amounts of data representing the prior knowledge about the interconnects, extracted from an analytical model and sparse amount of data extracted from a rigorous full-wave electromagnetic solver. In this way, the training of the ANN model is accelerated without significant loss in accuracy.**

Keywords— **Artificial neural networks (ANN), copper-graphene hybrid interconnects, per-unit-length resistance, variability analysis, training data.**

I. INTRODUCTION

In order to meet the high data rates and low energy-per-bit standards of sub-22nm technology nodes, various hybrid interconnect networks combining the electrical properties of multiple materials are currently being investigated. Among them, hybrid copper-graphene interconnects have shown some promising results for on-chip applications [1], [2]. In such interconnects, multiple layers of graphene act as barrier layers encapsulating the copper conductor. Due to the relatively large mean free paths of electrons in graphene and its high current carrying capacity, the resistance of the barrier layers come in parallel to that of the copper conductor, thereby effectively lowering the overall per-unit-length (p. u. l.) resistance of the interconnect. In order to quantify the performance of such novel hybrid interconnects, electronic design automation (EDA) tools need to be capable of quickly but accurately determining their p. u. l. parameters from their geometrical values.

Typically, full-wave electromagnetic (EM) solvers are used to extract the p. u. l. parameters from the geometrical and physical description of interconnect structures [3]. However, as the geometry of the interconnect structures change during design iterations, the EM solver has to be rerun. Given the exorbitant CPU run time for each EM solver run, this task quickly becomes computationally intractable. To mitigate this problem, surrogate models such as artificial neural networks (ANNs) have been employed [4]. ANNs employ flexible and nonlinear activation functions to characterize the functional mapping between the values of the geometrical parameters and the p. u. l. parameters of the interconnects [5]. Once trained, the ANN can be stored as a closed-form surrogate to the EM solver. Subsequently, ANN coefficients can then be repeatedly used to efficiently estimate the p. u. l. parameter values for different design scenarios. Unfortunately, ANNs require large sets of data extracted from full-wave EM solvers at excessive computational time cost for training.

In this paper, a methodology to accelerate the training of ANNs in order to quickly quantify the p. u. l. resistance of hybrid copper-graphene interconnects from the knowledge of the geometrical interconnect structures is developed. The proposed methodology begins by constructing an initial ANN that is trained using the data from an analytic model. The analytic model used is based on the Fuchs-Sondheimer and Mayadas-Shatzkes bulk, surface, and grain boundary scattering resistance models of copper combined with the scattering resistance model of graphene nanoribbons [6]. This analytic model represents the circuit designer's prior knowledge regarding the interconnect p. u. l. resistance and so the ANN is referred to as a prior knowledge ANN (PK-ANN). Importantly, this model being analytic, it can be quickly solved as compared to a full-wave EM solver to extract the requisite training data. Furthermore, in the work of [6], it has been shown that this analytic model is able to quantify the p. u. l. resistance of hybrid copper-graphene interconnects with a reasonable degree of accuracy. The ability to do so at extremely small time costs is the key attribute of the proposed methodology.

Next, in order to further enhance the accuracy of the PK-ANN, a second ANN is constructed. This ANN, referred to as a corrector ANN (C-ANN), models the error between the results of the PK-ANN and the EM solver. This error quantity, typically being small, ensures that the C-ANN can be trained using a small set of EM solver runs compared to the large number of runs required to train a conventional ANN. Finally, the sum of the outputs from the PK-ANN and C-ANN together provide an
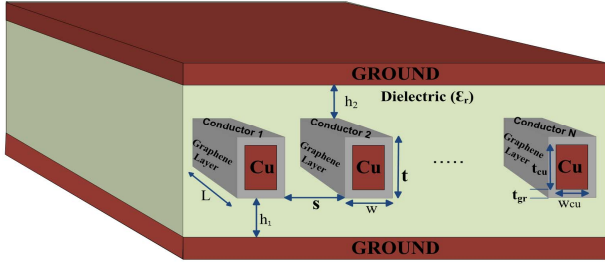
Fig. 1. Cross-section of copper-graphene hybrid interconnect network.

Fig. 2. Neural network architecture for PK-ANN showing input, hidden, and output layers.

accurate estimate of the p. u. l. resistance of hybrid copper-graphene interconnects. Thus, in this paper, prior knowledge of the interconnects is leveraged to expedite the training of ANNs without much loss in accuracy.

II. DEVELOPMENT OF THE PROPOSED PRIOR KNOWLEDGE BASED ACCELERATED ANN

Consider a hybrid copper-graphene interconnect network as shown in Fig. 1. Each conductor consists of a copper core and multiple graphene barrier layers encapsulating this core. Now, in order to model the impact of the geometrical parameters of the structure of Fig, 1 on the p. u. l. resistance, the proposed prior knowledge accelreated ANN model is adopted.

A. Constructing Prior Knowledge ANN (PK-ANN)

The proposed approach begins by constructing the prior knowledge ANN (PK-ANN). The PK-ANN has a three-layer structure as depicted in Fig. 2. The input variables $\lambda = [\lambda_1, \cdots, \lambda_{N_1}]$ represent the N_1 different geometric parameters of interest. In the second (hidden) layer, the weighted values of the inputs are gathered and processed using N_2 neurons. Finally, in the output layer, the weighted output of the neurons in the hidden layers are gathered and again processed using a single neuron. The output R represents the estimated p. u. l. resistance of the conductors of Fig. 1. Overall, the output R is mathematically expressed as

$$R = \sigma_{out}\left(\sum_{i=1}^{N_2}\omega_{i1}^{(2)}\sigma_{hi}\left(\sum_{j=1}^{N_1}\omega_{ji}^{(1)}\lambda_j + \omega_{0i}^{(1)}b_1\right) + \omega_{01}^{(2)}b_2\right) \quad (1)$$

where σ_{out} and σ_{hi} are the activation functions in the output layer and the i-th hidden layer neurons respectively, $\omega = [\omega_{11}^{(1)}, \cdots, \omega_{N_21}^{(2)}]$ represents all the synaptic weights, and the general synaptic weight $\omega_{ij}^{(k)}$ is the weight between the i-th neuron in the k-th layer and j-th neuron in the $k+1$-th layer. Moreover, the variables b_1 and b_2 refer to the bias values. The weights of (1) are optimized so that the result of the ANN closely matches the training data within a set error limit [5].

For the PK-ANN, the initial training data is extracted from an analytic model based on the Fuchs-Sondheimer and Mayadas-Shatzkes bulk, surface, and grain boundary scattering resistance models of copper and the scattering resistance of
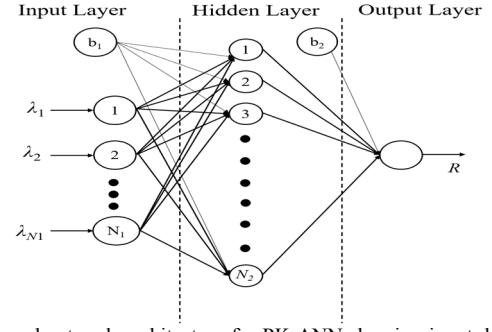
graphene nanoribbons [6]. As per this model, the equivalent p. u. l. resistance of the interconnects is given as [6]

$$\frac{1}{R} = \frac{1}{R_{Cu}} + \sum_{k=1}^{N_b}\frac{1}{R_{Gk}};$$

$$R_{Cu} = \frac{\rho_{bulk}(F_{FS}+F_{MS})}{wt}; \quad R_{Gk} = \frac{1}{2e^2 N_b N_c}\left(1 + \frac{L}{\xi_{eff}}\right) \quad (2)$$

In (2), R_{Cu} and R_{Gk} are the p. u. l. resistance due to the copper core and the k-th graphene layer, ρ_{bulk} is the resistivity of bulk copper, w and t are the interconnect width and thickness respectively, N_b is the number of graphene barrier layers, N_{ch} is the number of conduction channels per layer and ξ_{eff} is the effective mean free path of graphene barrier layer. The functions F_{FS} and F_{MS} are the Fuchs-Sondheimer and Mayadas-Shatzkes models for the Surface and grain boundary scattering mechanisms in copper expressed as

$$F_{FS} = 0.45\xi_{Cu}\left(1 - \rho_{Cu}\right)\left(\frac{w+t}{wt}\right);$$

$$F_{MS} = \left(1 - 1.5\phi + 3\phi^2 - 3\phi^3\ln\left(1 + \frac{1}{\phi}\right)\right)^{-1}; \phi = \frac{\xi_{Cu}R_f}{D_g(1 - R_f)} \quad (3)$$

where ξ_{Cu} is the mean free path of electrons in copper, R_f is the reflection coefficient, and D_g is the grain size of copper. The main advantage of the analytic model of (2) is that it offers reasonably accurate results but requires virtually negligible time costs to solve compared to a full-wave EM solver. Thus, it is possible to extract large amounts of data from (2) in order to train a reasonably accurate PK-ANN at very low time costs.

B. Constructing Corrector ANN (C-ANN)

In this work, to enhance the accuracy of the PK-ANN, a corrector ANN (C-ANN) is constructed. The C-ANN too has the same basic structure as shown in Fig. 2 with the exception that the output is in the form

$$\hat{R} = R_{EM} - R \quad (4)$$

where R_{EM} is the p. u. l. resistance value obtained from the EM solver and R is the estimate of the same obtained from the PK-ANN. It is understood from (4) that the variance of the C-ANN output can be expressed as [7]

TABLE I: Value of Correlation Coefficient of Output of PK-ANN

	Value of ANN training + testing samples (N_s)					
	100	200	300	500	600	800
Correlation coefficient	0.782	0.971	0.967	0.956	0.961	0.958
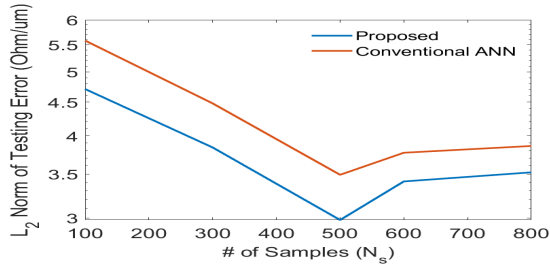
Fig. 3. L_2 norm of the testing error for the proposed PKA estimator and the conventional ANN with respect to the number of samples.

$$Var\left(\hat{R}\right) = Var\left(R_{EM}\right) + Var\left(R\right) - 2Cov\left(R_{EM}, R\right) \qquad (5)$$

Now, because the error of (4) is typically small, the correlation coefficient of R_{EM} and R tends to be closer to 1. Under this condition, based on (5) the variance of the C-ANN output will approach zero. Because of this reason, the C-ANN can be trained using very few runs of the full-wave EM solver.

C. Combining PK-ANN and C-ANN

Based on (4), an estimator of the p. u. l. resistance of hybrid copper-graphene interconnects is designed to be the sum of the outputs from the PK-ANN and C-ANN. This estimator is called the prior knowledge based accelerated (PKA) estimator. Notably, the total time cost required to train the PKA estimator is the sum of the time cost required to train the PK-ANN and C-ANN. Given that both these individual time costs are very small due to the analytic nature of the model of (2) and the small variance of the output of C-ANN in (5), their sum is expected to be small as well. Thus, the overall time cost to train the PKA estimator is usually smaller than that required to train a conventional ANN.

III. Numerical Results and Discussions

In this section, a 3-line hybrid copper-graphene interconnect network is considered. The geometrical and physical parameters of interest are [w, t, s, h_1, t_{gr}] (see Fig. 1). The nominal values considered for these parameters are [13, 27.3, 12, 27, 0.8] (all in nm), with an assumed variation of +/- 10%.

In this example, the proposed PKA estimator and a conventional ANN model are constructed. When constructing the PKA estimator, the PK-ANN is trained using 4000 data samples extracted from the analytic model of (2) in order to achieve L_2 training and testing error norms of below 0.15 $\Omega/\mu m$. Only a single hidden layer with 10 neurons is used with the activation functions as the hyperbolic tangent function. The time cost of extracting each data sample from the analytic model of (2) is only 50 μs (which is more than four orders of magnitude faster compared to the EM solver (Ansys Q3D Extractor)). For training the C-ANN and the conventional

TABLE 2: CPU Cost Comparison

	Proposed PKA Estimator	Conventional ANN	EM Solver
CPU Time	~35 hours	50 hours	50 hours

ANN, data samples are extracted from the EM solver. The number of data samples used is varied as N_s = [100, 200, 300, 500, 600, 800] where half of the samples served as training samples while the other half as testing samples. As before, only a single hidden layer is required for the C-ANN and conventional ANN. For the different values of N_s, the correlation coefficient between the output from PK-ANN and the output from the conventional ANN is calculated using 5000 Monte Carlo samples and the results are listed in Table I. It is seen from Table I that when sufficient samples are taken (i.e., $N_s > 100$), the correlation coefficient is very close to 1, thereby indicating the reasonable accuracy provided by the PK-ANN. Notably, the PK-ANN achieves accurate results at a combined training and testing CPU cost of only 0.2 seconds whereas the conventional ANN requires roughly 10 hours to extract and fit data for N_s = 100 samples. Next, the scaling of the L_2 testing error norms w. r. t. N_s for the proposed PKA estimator and the conventional ANN is shown in Fig. 3. From Fig. 3, it is noted that the proposed PKA estimator is consistently able to achieve a lower error for same N_s than the conventional ANN. In fact, to reach the same error norm of 3.5 $\Omega/\mu m$, the proposed PKA estimator needs roughly 350 full-wave EM solver runs compared to the 500 needed by the conventional ANN. Beyond 500 samples, both the PKA and the conventional ANN overfit the data as seen by the increasing error.

IV. Conclusion

In this work, a prior knowledge driven approach to accelerate the training of ANNs is proposed. This approach efficiently estimates the p. u. l. resistance of hybrid copper-graphene interconnects using less expected EM solver runs as compared to traditional ANN based approaches.

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