Deep Learning Enhanced Hybrid BEM-rMLNCA Method for Efficient Power Cable Crosstalk Prediction

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Abstract **–** This paper presents a deep learning-assisted hybrid Boundary Element Method (BEM)-recompressed Multilevel Nested Cross Approximation (rMLNCA) algorithm for efficient and accurate crosstalk prediction. This hybrid approach aims to combine the physics-based precision of BEM with the compression efficiency of rMLNCA and the nonlinear learning capability of deep neural networks (DNN) for high-fidelity modeling with reduced computational requirements. Under this proposed method, three parameters are predicted for crosstalk: Near-End Crosstalk (NEXT), Far-End Crosstalk (FEXT), and Common-Mode Current (CMC) measurement. The impedance and coupling parameters are computed using BEM, while rMLNCA decomposes and recompresses the far-field matrices into low-rank admissible blocks, reducing both memory and time significantly. It improves predictive accuracy further by learning nonlinear relationships among geometric, material, and frequency-dependent features using an optimized deep neural network architecture. The suggested model has high predictive consistency with the 5-fold cross-validation R^2 of 0.9736 ± 0.0053. Final evaluation results showed that there is strong accuracy, as depicted by R^2 and MAPE values for NEXT, FEXT, and CMC of 0.9707/15.10%, 0.9602/11.11%, and 0.9750/8.19%, respectively, validating generalization performance.

Index Terms **–** Boundary element method, deep neural network, far-end crosstalk, near-end crosstalk, power cable, recompressed multilevel nested cross approximation.

I. INTRODUCTION

Crosstalk parameter estimation plays a critical role in electromagnetic compatibility. If the interference of neighbor cables degrades signal quality, it also generates difficult-to-remove Far-End Crosstalk (FEXT) in high-speed data transmission [1, 2]. In particular, cables like LIFY and AWG23 have been designed to be resistant against electromagnetic interference for control and data systems [3]. However, compared to the extensive studies done on external interference, internal crosstalk within twisted pairs remains limited [4].

Impedance matrices dealing with crosstalk and current distribution are mostly derived by analytical methods which are then numerically accelerated by sophisticated numerical techniques like integral equation-fast Fourier transform [5] and adaptive integral method [6]. The methods mentioned improve calculation efficiency, however, they remain limited in terms of nonlinear memory computations. Advanced numerical techniques, including finite difference method [7], and method of moments (MoM) [8], have significantly improved the accuracy of crosstalk analysis compared to earlier methods. Conductor partitioning-based approaches [9], volumetric finite element method [10], and Boundary Element Method (BEM) [11] have very high computational burdens, whereas MoM remains the most efficient among the methods dealing with a complex geometry. The adaptive cross approximation (ACA) technique efficiently reduces the computational cost of singular value decomposition through low-rank compression, thus proving ideal for large-scale electromagnetic and multiconductor transmission line (MTL) analyses [12].

Low-rank approximations of far-field impedance matrix interactions are effectively compressed with controlled error tolerance. Methods such as ACA [13] and Hybrid Cross Approximation [14] enhance stability but are without hierarchical organization, limiting the reduction in complexity. Exploiting the nesting property of Lagrange polynomials allows the construction of hierarchical H^2-matrices [15] that further improve computational efficiency. Further advances in fast algorithms by kernel-independence and nesting have resulted in direct H^2-matrix formulations with reduced conversion complexity from $O(N \log N)$ [16]. Notably, two kernel-independent methods (nested equivalent source

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approximation and nested skeletonization) achieve this by using multilevel equivalent sources and proxy surface sampling, respectively [17].

Nested cross approximation (NCA) is an algebraic method that constructs hierarchical low-rank bases with near-linear memory and computational cost using only a few matrix samples [18]. However, the existing algebraic fill strategies rely on globally nested bases; as the problem size increases, the far-field blocks grow fast and, hence, the strategy becomes inefficient. On this account, a deep learning-assisted approach is developed by recursively performing the recompression on the local admissible blocks so that this approach scales better for electrically large problems.

The present study describes a deep learning-assisted hybrid method that incorporates a DNN with BEM and Multilevel Nested Cross Approximation (rMLNCA) for efficient and accurate crosstalk prediction in power cables. DNN enhances the rMLNCA process in computational efficiency, stability, and scalability for crosstalk analysis. With its pattern recognition capability, it refines the numerical compression kernel to achieve high-fidelity modeling of complex coupling behavior. This approach yields a hybrid DNN-BEM-rMLNCA with near-linear computational complexity, significantly reducing the computational burden compared with traditional approaches. The model makes effective predictions of Near-End Crosstalk (NEXT), Far-End Crosstalk (FEXT), and Common-Mode Current (CMC). Validation was performed against the conventional nested cross approximation and the transmission line matrix method.

The paper is organized thus: Theoretical background and simulation setup for single- and multiwire crosstalk are presented in section II, while section III describes the hybrid DNN-assisted model. Section IV presents the results and analysis, and section V concludes the study.

II. PROPOSED MODEL DESCRIPTION

A. Numerical model

A.1. Single-to-single cable

This research is based on single-to-single-line parameter estimation for crosstalk analysis of an AWG23 single-core cable. One wire is used as an aggressor and the other as a victim. Both NEXT and FEXT crosstalk on the victim line are calculated and confirmed. Table 1 provides the cable parameters while Fig. 1 represents the cross-sectional model and the circuit schematic where P_1-P_2 are NEXT ports and P_3-P_4 are FEXT ports.

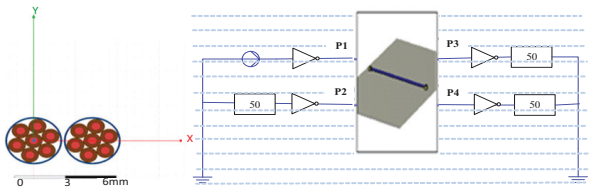


Fig. 1. Single-line crosstalk simulation model.

Table 1: Single wire parameter (AWG)

Parameter	Value
Relative distance between cables d	5 mm
Height above the ground h	50 mm
Single core conductor radius r_1	0.286 mm
Insulation thickness of single core wire t_1	0.19 mm (PE)
Termination resistance	50 Ω
Line length 1	1 m

A.2. Single cable to twisted pair

The analysis in this part is focused on the parametric study of the twisted LIFY cable. The cables are multistrand, multicore composite and, for crosstalk analysis, a singlecore wire is considered as the aggressor and the twisted pair as the victim. The parameters to be varied are presented in Table 2, and the cable model is depicted in Fig. 2. Ports P_1-P_3 illustrate NEXT on lines 1–3, and P_4-P_6 refer to FEXT on the same lines.

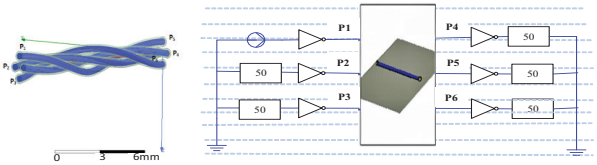


Fig. 2. Simulation of twisted pair crosstalk.

Table 2: Twisted wire constraints (LIFY)

Parameter	Value
Relative distance between cables d	5 mm
Height over the ground h	50 mm
Single core conductor radius r_1	0.286 mm
Insulation thickness of single core wire t_1	0.19 mm (PE)
Twisted pair radius r_2	0.50 mm
Insulation thickness of twisted pair t_2	1.0 mm (PE)
Termination resistance	50 Ω
Line length 1	1 m

B. Deep learning model

This paper proposes a hybrid algorithm aided by deep learning to predict power cable crosstalk with high accuracy. The hybrid model (Fig. 3) integrates a 100-layer deep neural network with the BEM-rMLNCA numerical method. It utilizes the shape and material properties to predict NEXT and FEXT. The model, which was trained on 1000 samples and stabilized with batch normalization and dropout, achieved a speed-up of the calculation time by 97.2%, a reduction of the operational complexity by 87.5%, and the total time for the analysis of only 2.8 s, about 35 times faster than conventional methods.

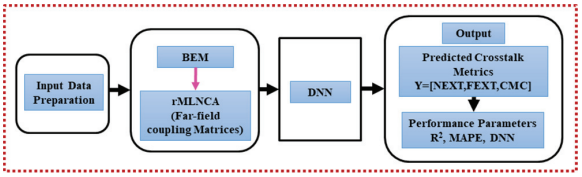


Fig. 3. DNN proposed method.

III. DNN ASSISTED BEM-RMLNCA ALGORITHM FOR POWER CABLE CROSSTALK

A. Implementation of DNN-BEM-rMLNCA algorithm for power cable crosstalk

BEM discretizes only boundaries, not the full domain. To handle dense matrices in complex problems, we introduce a hybrid rMLNCA for cable crosstalk that has a low-rank approach using minimal entries to approximate full information. A low-rank matrix S is represented by

$$S \in (UV^T)^{p\times q}. \tag{1}$$

The basis function is discretized by MoM for cable crosstalk interference parameters. The main purpose of the basis function is to discretize the number of segments (wires) in the MTL accordingly. The total number of wires is the sum of $N^{(r)}$, where $r = 1,2\ldots$M and $N =$ number of wires. The basis function for cable crosstalk based on rMLNCA is:

$$E_z(r) = \sum_{i=1}^{M}\sum_{r=1}^{N^{(r)}} \alpha_r g_r(r), \tag{2}$$

$$[S]^{p\times q} = [\widetilde{S}]^{p\times q} = [U]^{p\times r}[V]^{r\times q}. \tag{3}$$

The test functions are chosen within a weighted residual-Galerkin function to meet boundary requirements and linear independence, and use the same basis functions to approximate the solution to ensure numerical stability and weighted residual minimization convergence. The testing function w_j for the M-conductor cable crosstalk is:

$$\langle W_j, E\rangle = \sum \langle W_j, f_e(J_r, g_r)\rangle; \quad J = 1,2,\ldots,M. \tag{4}$$

The testing function based on the rMLNCA becomes:

$$[E_r] = [S_{pq}][I_r] = [U_{pr}][V_{rq}][I_r]. \tag{5}$$

Near-end crosstalk: Crosstalk occurs at the near end of the aggressor line closest to the driver. NEXT in terms of voltage is given by:

$$E_{Near} = \sum_{i=1}^{M}\sum_{r=1}^{N^{(r)}} U_{pr}^{(i)} S_r^{(i)} (V_{rq}^{(i)})^T \cdot I_{agg}(t-\tau_{Near}). \tag{6}$$

Far-end crosstalk: FEXT occurs at the end of the victim line opposite to the aggressor driver. The rMLNCA based approximation is:

$$E_{Far} = \sum_{i=1}^{M}\sum_{r=1}^{N^{(r)}} U_{pr}^{(i)} S_r^{(i)} (V_{rq}^{(i)})^T \cdot I_{agg}(t-\tau_{Far}). \tag{7}$$

The common mode measurement induced on a victim cable due to an aggressor's CM current is:

$$I_{CM} = \sum_{i=1}^{M}\sum_{r=1}^{N^{(r)}} U_{pr}^{(i)} \sum (V_{rq}^{(i)})^T \cdot I_{agg}(t-\tau_{CM}). \tag{8}$$

In equation (9), the convergence criterion epsilon ε is evaluated using the L_2 norm (Euclidean norm) of the residual vector. The convergence ε for the proposed solution is:

$$\|S - \tilde{S}\| \le \varepsilon. \tag{9}$$

Adaptive tree depth is determined by crosstalk convergence, with recursive subdivision terminating at Level 8 when successive changes fall below a predefined threshold. The resulting octa-level tree achieves a compression ratio of 1:775 and a basis function reduction factor of 0.612012. Tables 3 and 4 show the details.

Table 3: Average reduction order of matrix assembly

Matrix Assembly	Average Order
122575	1.386382
155996	1.371161
169755	1.355393
183034	1.334839
196787	1.319798
225281	1.297659
242185	1.289720
257994	1.282211
273871	1.275396
286440	1.269410

Table 4: Computation of basis function for power cable

Tetrahedra	Basis Function Order	Memory	Solution Time	Adaptive Passes
286440	0	299 MB	3 min	17
355596	1st	480 MB	9 min	13
293764	2nd	619 MB	10 min	12
122575	Mixed	0.765 KB	10 s	9

In the DNN method, the adjoined conditions limit the constraints of the far-field coupling matrix. The convergence is monitored for 50 epochs. Mean Absolute Error (MAE) decreases from ∼0.95 to less than 0.2 at around epoch 20 and remains at about 0.05 after 40 epochs, thus, the network can be considered effectively trained. The simultaneously training and validation error curves also suggest that the model generalizes well (Fig. 4).

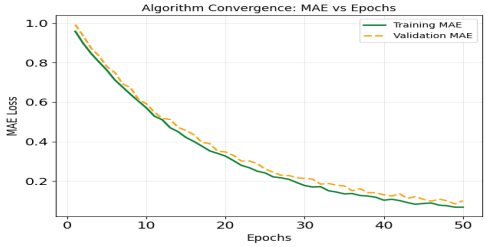


Fig. 4. MAE convergence of proposed algorithm.

Frobenius relative error between reference A_{gt} and predicted $\hat{A}$ along with the element-wise error $|\hat{A} - A_{gt}|$ of a rank- 816×16 far-field matrix is depicted in Fig. 5. The network accurately learns the lowrank features. On average, a ∼10% mean relative Frobenius error is achieved for 1000 test samples. The basic algorithmic flowchart is demonstrated in Fig. 6.

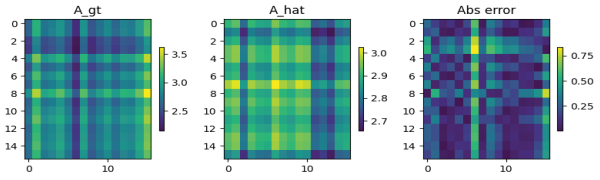


Fig. 5. Relative Frobenius error of proposed algorithm.

IV. RESULTS AND DISCUSSION

A. Power cable crosstalk analysis

In this section, a deep neural network prediction for power cable crosstalk analysis based on BEM-rMLNCA is presented. A HFSS-IE solver is used for the numerical solution of the proposed model layout of cables to build cable simulation models independently. The hybrid solver is used to compute the S-parameters from the computations of a low-rank matrix or rank deficient matrix. Simulated data is extracted, and then trained using dense DNN to predict the crosstalk in the power cable. Data normalization takes place.

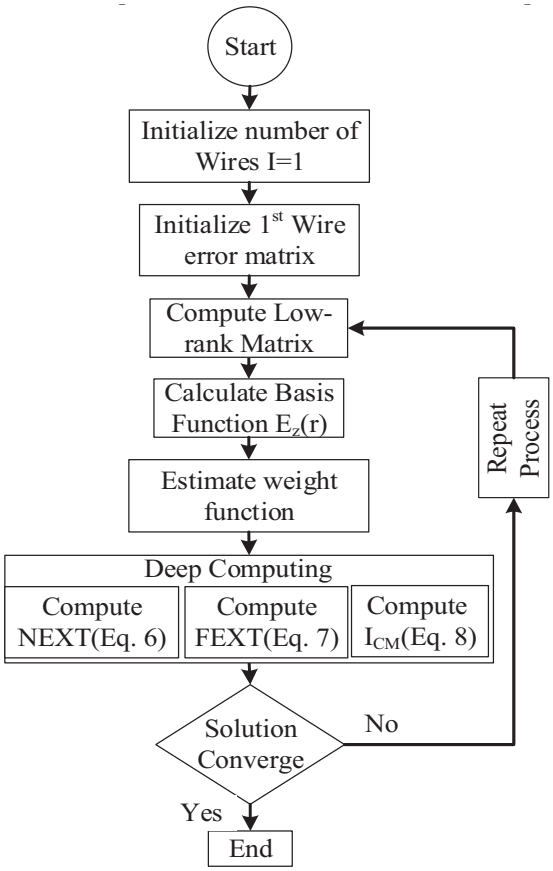


Fig. 6. Flowchart of DNN hybrid BEM-rMLNCA algorithm.

A.1. Near end crosstalk

Figure 7 presents the measured and predicted NEXT across 0.1–1 GHz. NEXT decreases with frequency, from approximately 0.7–0.9 dB at 0.1 GHz to 0.3–0.4 dB around 0.5 GHz, and down to about 0.05–0.2 dB at 1 GHz. The predicted values, shown as red crosses, trajectory well with the measured data, depicted as blue dots, except for minor deviations in the low-frequency region where NEXT is relatively high and more variable. The model accurately captures the frequency-dependent coupling behavior. The frequency-averaged relative error amounts to 0.032%, and the computational efficiency is 98%. Hence, the plot shows strong agreement between the predicted and actual NEXT, further confirming the reliability of the model over the operating band.

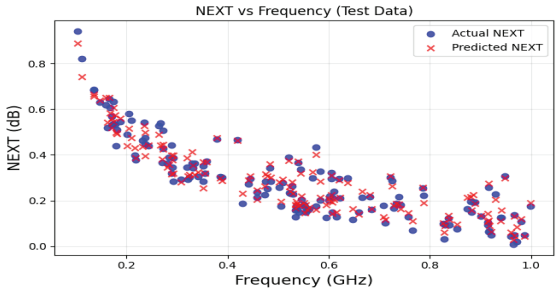


Fig. 7. Near-end crosstalk estimation.

A.2. Far end crosstalk

Figure 8 illustrates the variation of FEXT with frequency for a multiconductor power cable transmission system. Analysis covers frequencies from 0.1 to 1 GHz, where FEXT values range between 0.1 dB and 0.85 dB across 97 test cases. The results reveal an inverse relationship (FEXT decreases to around 0.25 dB as frequency rises), reflecting reduced electromagnetic coupling at higher frequencies. The comparison between predicted (red crosses) and measured (blue dots) values shows close alignment, with an average relative error 0.09%. Additionally, the matrix compression technique enhances computational efficiency by nearly 95%. This predicted computational efficiency gain demonstrates reduced runtime and increased solver throughput. Overall, the strong alignment between simulated and predicted results highlights the model's reliability and accuracy in estimating crosstalk within complex cable systems, achieving an effective balance between precision and computational speed.

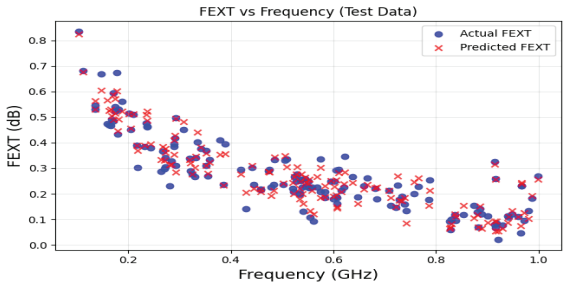


Fig. 8. Far-end crosstalk estimation.

A.3. Common mode current measurement

Figure 9 presents a comparison of the Common Mode Current test dataset values between 0 and 1 GHz that were both measured and predicted. Measured data (blue circles) and model predictions (red crosses) show the same rising trend with CMC increasing from about 0.05 A at 0.05 GHz to around 1 A at 1 GHz. The close matching indicates that the model performance is strong which is reflected by $R^2 = 0.9750$, root mean square error (RMSE) = 8.29%, and mean absolute percentage error (MAPE) = 8.19%. The RMSE is normalized by the mean absolute value of the reference crosstalk over the frequency band. These findings confirm the model's capability to grasp the nonlinear, frequency-dependent coupling behavior of the power cable. The minor differences at higher frequencies may be due to measurement uncertainty or boundary simplifications in the hybrid solver. The compressed matrix achieves 97% reduction with only ∼3% precision loss, thus the relative error is very small (0.05%) and the steady state behavior is stable. The steady-state behavior in this broadband frequency-domain analysis refers to the crosstalk and CMC's stabilized sinusoidal response at each frequency following the decay of all transient effects. Consequently, the measurements and predictions are in close agreement. Figure 10 shows the comparison of crosstalk based on DNN.

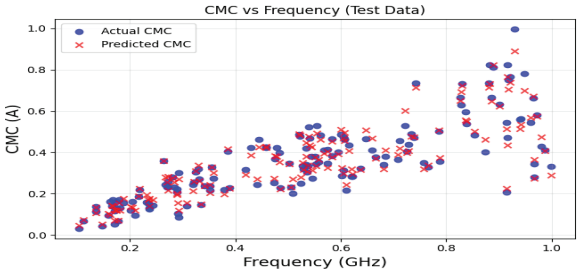


Fig. 9. Common mode current measurement for power cable.

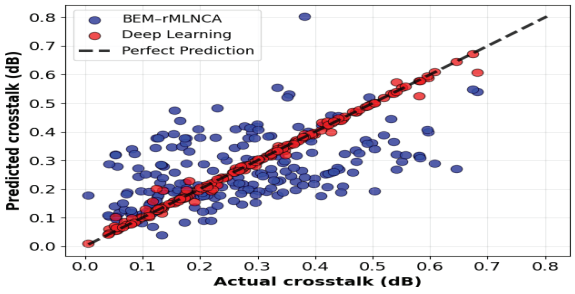


Fig. 10. Crosstalk comparison of the proposed algorithm.

B. Computing parameters

For the performance evaluation of the proposed algorithm, memory usage, CPU time, error, and accuracy were compared. Table 5 summarizes the memory and runtime performance, while Fig. 11 shows the error and accuracy plots. The combined analysis confirms strong predictive capability for key electromagnetic parameters. For NEXT, the model obtained $R^2 = 0.98$, while the errors are low: RMSE = 2.1%, MAPE = 3.5%. In the case of FEXT, it maintained reliable performance

Table 5: Computational parameters of proposed algorithm

Matrix	Hybrid Method		Traditional Method [20]		Transmission Line Matrix [19]	
Assembly	Memory (KB)	CPU Time	Memory (MB)	CPU Time	Memory (MB)	CPU Time
122575	1.36	2	135	11	135	14
155996	1.28	3	225	13	232	19
169755	0.990	3	296	22	299	27
183034	1.110	4	334	24	367	32
196787	1.1	4	488	26	498	38
225281	0.550	4	499	31	556	42
242185	1.29	5	545	39	667	46
257994	0.747	5	676	50	812	59
273871	0.875	6	787	54	987	67
286440	0.679	7	989	65	1089	80

with $R^2 = 0.94$, RMSE = 3.8%, MAPE = 5.2%, confirming that accuracy is consistent for both outputs.

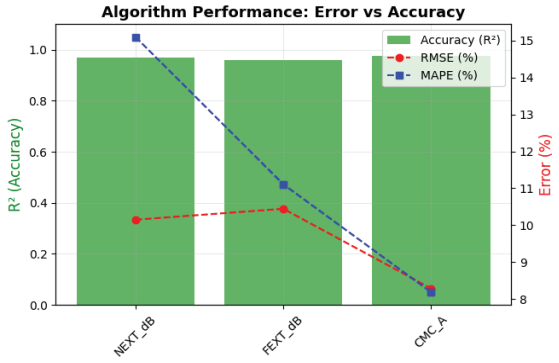


Fig. 11. Error vs Accuracy analysis of proposed algorithm.

V. CONCLUSION

In this paper, deep learning assisted hybrid BEM-rMLNCA is presented for complex electromagnetic coupling analysis to predict power cable crosstalk characteristics. The hybrid algorithm is a good approximation approach for far-field matrices entries. Numerical evaluations demonstrated excellent predictive performance achieving cross-validation R^2 values above 0.97 while maintaining low MAPE across the measurement parameters of NEXT, FEXT, and CMC current. Results identified that the hybrid algorithm's computational efficiency is about 97% and matrix compression order is 1:125, significantly reducing memory and processing requirements. These results thus confirm the capability of the model in capturing the complex coupling effects and frequency dependent behaviors in MTL. The DNN hybrid approach offers highly reliable, scalable, and efficient solutions for complex electromagnetic coupling analysis. The limitation of the proposed approach depend on data accuracy and error propagation from BEM-rMLNCA approximations and scalability issues for large multiconductor systems.

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