ITU Journal of Wireless Communications and Cybersecurity

ITU/JWCC

Prediction of Power Amplifier Performance via Fine and Coarse Modeling Along with Deep Neural Network

Lida Kouhalvandi[1], **Mohammad Alibakhshikenari**[2], **and Serdar Ozoguz**[3]

[1] Department of Electrical and Electronics Engineering, Dogus University, Istanbul, 34775, Turkey
[2] Department of Electronics Engineering, University of Rome Tor Vergata, Rome, 00133, Italy
[3] Department of Electronics and Communication Engineering, Istanbul Technical University, Istanbul, 34469, Turkey

Abstract: The power amplifier (PA) is a nonlinear design for which an accurate characterization is required for modeling and optimizing effectively. To tackle this difficulty, we present a method based on the fine and coarse modeling approach along with the implementation of deep neural networks (DNNs). For this case, firstly the executed transistor is modeled with the X-parameters and the DNN, as the 'fine modeling'. Then, the S-parameters are modeled with the help of configured hidden-layer structure at the previous step as the 'coarse modeling' leads to facilitate the overall PA sizing. Finally, the PA is modeled through the optimized DNN, which leads to estimating the performances of PA at the extended frequency in terms of S-parameters, output power, power gain, and efficiency. The presented fine and coarse modeling is powerful enough to configure the hidden-layer configuration of DNNs without any need for other optimization methods for determining the number of hidden layers with neurons in each one. The presented methodology is validated by designing and optimizing a PA with a power gain of more than 11 dB and a power-added efficiency of around 60% operating with 600 MHz band frequency.

Keywords: Fine and coarse modeling, deep neural network, optimization, power amplifier.

Derin Sinir Ağı Tabanlı İnce ve Kaba Modelleme Yoluyla Güç Kuvvetlendirici Performansının Tahmini

Özet: Güç kuvvetlendiricileri (GK), tasarımında yüksek doğruluklu bir karakterizasyonun kritik öneme sahip olduğu lineer olmayan bir devre bloğudur ve zorlayıcı isterlere göre tasarlanması için etkin bir şekilde modellenip optimize edilmesi gerekmektedir. Bu amaçla, öncelikle yapıda kullanılan transistörün X parametreleri ve DNN kullanılarak "ince modeli" elde edilir. Ardından, önceki adımda yapılandırılmış gizli katman yapısıyla transistörün bu sefer S parametreleri elde edilir, çünkü bu "kaba model" genel PA boyutlandırmasını kolaylaştırmaktadır. Son olarak, GK, optimize edilmiş DNN aracılığıyla modellenir ve bu da GK'nın genişletilmiş frekanstaki performanslarının S parametreleri, çıkış gücü, güç kazancı ve verimlilik açısından tahmin edilmesine olanak tanır. Önerilen ince ve kaba modelleme yöntemi, DNN'lerin gizli katman yapılandırmasını belirlemek için yeterli olup, gizli katman sayısı veya her katmandaki nöron sayısı gibi hiperparametreleri belirlemek için ek bir optimizasyon yöntemine ihtiyaç duymamaktadır. Sunulan yöntem, 600 MHz bant frekansında çalışan, 11 dB'den fazla güç kazancı ve yaklaşık %60'lık güç eklenen verimliliğe sahip bir GK'nin tasarlanması ile doğrulanmıştır.

Anahtar Kelimeler: İnce ve kaba modelleme, derin sinir ağı, optimizasyon, güç kuvvetlendirici.

THEORETICAL PAPER

Corresponding Author: Serdar Ozoguz, ozoguz@itu.edu.tr

Reference: L. Kouhalvandi, M. Alibakhshikenari, and S. Ozoguz, (2025), "Prediction of Power Amplifier Performance via Fine and Coarse Modeling Along with Deep Neural Network," *ITU-Journ. Wireless Comm. Cyber.*, 2, (1) 45–50.

Submission Date: Mar, 14, 2025
Acceptance Date: Mar, 18, 2025
Online Publishing: Mar, 28, 2025

1 INTRODUCTION

With the exponential advances in wireless communication systems, high-performance power amplifiers (PAs) for transmitting signals are becoming necessary [1] and the bandwidth of these systems is increasing day-by-day [2]. Hence, designing and modeling PAs require diverse techniques and topologies to meet the targeted specifications [3]. Recently, various optimization methods have been introduced for the accurate modeling of PAs including active and passive components. Among the diversely presented methods, the neural networks (NNs) are used for modeling the PAs which are able to approximate the nonlinear functions accurately [4].

In [5], a signal reconstruction deep residual neural network is introduced for digital pre-distortion (DPD) linearization which results in generating the out-of-band spectrum. The mixed-precision neural network is employed in [6] for energy-efficient DPD which reduces the computational complexity to the greatest degree. The convolutional neural network is introduced in [7] for modeling the PA with low computational complexity. In another study, [8], the deep neural network (DNN) is used for reducing the training time with the help of transfer learning. The recurrent neural network as another type of NN is used in [9] for behavioral modeling of PA. In [10], the DNN is executed for modeling and sizing the PA through the long short-term memory (LSTM)-based technique.

The NN can also be used for modeling the active device that in [11], it is employed for generating an automated optimization process. In summary, various methods are also introduced for modeling the transistors through NNs [12]. As it is obvious, starting the optimization process of PA from the transistor level is significant enough [13]–[15]. For this case, we propose an intelligence-based optimization method based on firstly modeling the high-electron-mobility transistor (HEMT) through the X-parameters with DNN as the 'fine modeling'. Afterward with the trained network, focus on the structure of hidden layers, a new DNN is constructed with the S-parameters of PA in which the constructed DNN is as the 'coarse modeling'. Finally, with the configured DNN in which the number of hidden layers with the number of neurons are known from the previously constructed DNNs, a new DNN is trained for optimizing the PA in terms of the S-parameters (i.e., S_{11}, S_{22}, S_{21}), power gain (G_p), output power (P_{out}), and power added efficiency (PAE). The proposed methodology is executed in a fully automated way leads to optimize design parameters of any PA that result in high-performance outcomes. In this study, we design and optimize a PA operating from 1.7 GHz to 2.3 GHz in which Gallium nitride (GaN) HEMT is used as an active device.

This work is organized as follows: Section 2 is devoted to presenting the methodology that is based on the fine and coarse modeling in which the DNNs are constructed. The

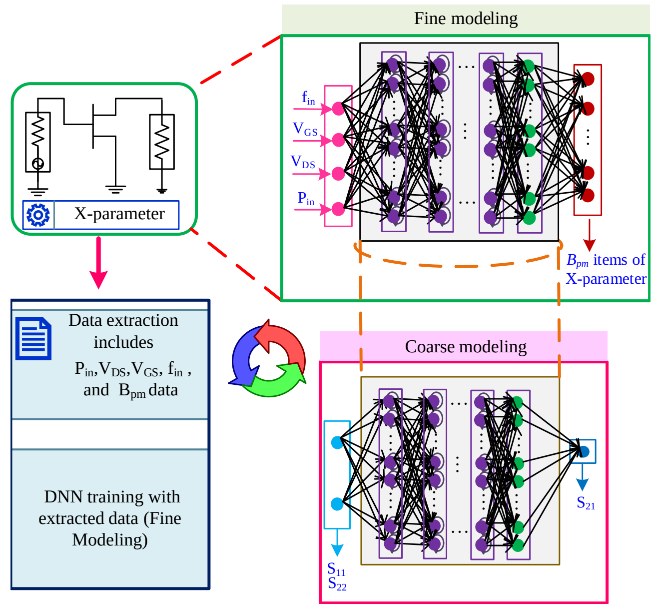

Fig. 1 A flowchart of presented fine and coarse modeling approcah in this study.

effectiveness of the proposed approach is validated by designing and optimizing a PA with 600 MHz bandwidth and the related simulation results are presented in Sec. 3. Finally, Sec. 4 concludes this study.

2 PROPOSED METHODOLOGY BASED ON FINE AND COARSE MODELING ALONG WITH TRAINING DNNs

As previously presented, the DNN method is strong enough for learning nonlinear behavior between input and output corresponding data. For this case, we propose an automated methodology that is based on i) modeling HEMT device through X-parameters (fine modeling), ii) modeling PA with S-parameters with the help of constructed DNN at the previous step (coarse modeling), and iii) optimizing the PA in terms of one-tone continuous wave (CW) performances. For all the trained DNNs, the normalized root mean square error (RMSE) is a factor for calculating the convergence of NN and also the rectified linear unit (ReLU) function is executed as the activation function. This section is devoted to presenting the proposed methodology in which the flowchart of 'fine and coarse modeling' through DNNs is depicted in Figure 1.

2.1 Fine Modeling

X-parameters are frequency-dependent parameters, highly accurate, and widely used modeling tools for nonlinear high-frequency structures. It consists of three additional terms as X^F, X^S, and X^T in the output spectrum. X^F captures a large signal harmonic response and X^S with X^T captures the small signal sensitivity by representing the incident and scattered waves. Functions for B_{pm} are reflected waves (labeled with port *p* and harmonic *m*), and are given small extraction tones as A_{qn} (labeled with port *q* and harmonic *n*). The detailed definitions are presented in (1) and (2).

$$B_{pm} = X^{(F)}_{pm}(|A_{11}|)P^{m} + X^{(S)}_{pm,qn}(|A_{11}|)P^{m-n}A_{qn} + X^{(T)}_{pm,qn}(|A_{11}|)P^{m+n}A^{*}_{qn} \quad (1)$$

where,

$$P = \frac{A_{11}}{|A_{11}|} \quad (2)$$

As the first step of optimization, the GaN HEMT transistor is modeled through the LSTM-based DNN in which the X-parameters are used as a dataset for training. As Figure 1 shows in the fine modeling step, the input layer of LSTM-based DNN includes specification as the input frequency (f_{in}), input power (P_{in}), gate-source (V_{gs}) and drain-source (V_{ds}) and the output layer is the B_{pm}. Here, the LSTM-based DNN is constructed and the RMSE specification is considered. If this specification is suitable enough, then the constructed hidden layers (including the number of LSTM layers with neurons in each one) are fixed for modeling the next DNNs.

2.2 Coarse Modeling

After modeling the HEMT device through the X-parameters and achieving the hidden-layer structure, this configuration of hidden layers is employed for modeling the PA through S-parameters. The general structure of LSTM-based DNN used for coarse modeling is depicted in Figure 1. For this kind of network, the input layer includes S_{11} and S_{22} specifications and the output layer represents S_{21} result. This step of modeling will lead to improving the optimization process in which the overall performance of PA will be enhanced based on S-parameters and one-tone continuous wave (CW) performances in the next step.

2.3 Overall PA Optimization

After completing the fine and coarse modeling, the PA must be optimized in terms of existing parameters (here, capacitor (C) and inductor (L)) to achieve high-performance outcomes in terms of S_{11}, S_{22}, S_{21}, G_p, P_{out}, and PAE specifications. Figure 2 shows the DNN structure leading to i) optimizing the PA in terms of inserted design parameters, and ii) estimating the output specifications at the determined frequencies. For this kind of DNN, the hidden-layer structure is the one achieved from fine modeling.

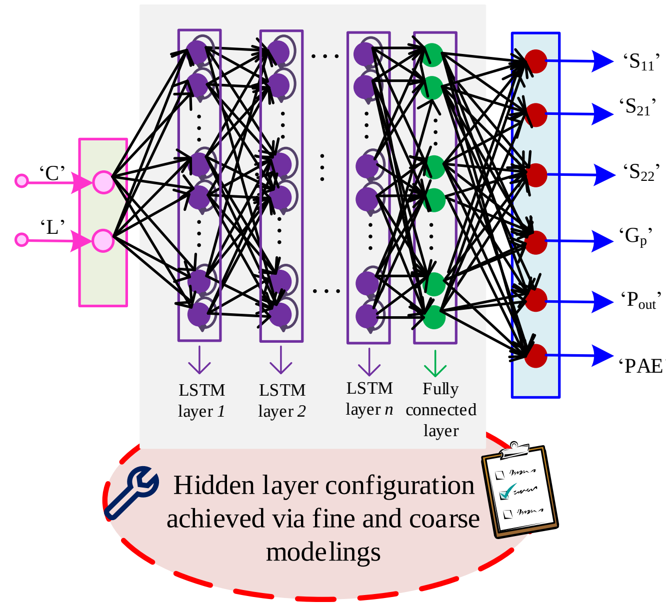

Fig. 2 Structure of LSTM-based DNN for optimizing the PA and achieving the optimal design parameters along with predicting the extended frequencies.

3 SIMULATION RESULTS

For executing the proposed methodology, a CPU environment with an Intel Core i7-4790 CPU @ 3.60 GHz and 32.0 GB RAM is prepared first. Then, a GaN HEMT transistor as an active device namely 'Ampleon CLF1G0060-10' is selected. For the presented procedure, the automated environment is generated by the combination of 'Keysight ADS' and 'MATLAB' as the electronic design automation tool and numerical analyzer, respectively. For all the trained DNNs, the solver is set to 'adam' and 'gradient threshold' is set to 1. This section describes the practical implementation of the proposed method for the PA operating with 600 MHz band frequency.

As the first step, the fine modeling is executed based on the X-parameters generated by the f_{in}, P_{in}, V_{gs}, V_{ds} [16], and B_{pm} specifications as presented in Eq. (1). Here, the modeling is executed for *p*=2 and *m*=5. With the help of 500 data (achieved from random iteration), the LSTM-based DNN is trained results in the normalized RMSE value presented in Figure 3. As it is obvious, the trained DNN achieved 0.087 RMSE value when the number of hidden layers is 4 with 200 neurons in each one.

Afterward, the coarse modeling is executed with the help of configured PA through the simplified real frequency technique [17] and also by the generated gate and drain impedances through the load-pull simulation. Figure 4 presents the configured PA that input and output matching networks include 4-LC with 2-LC ladders, respectively. For the presented PA, Rogers RO4350B with ε_r=3.66 and

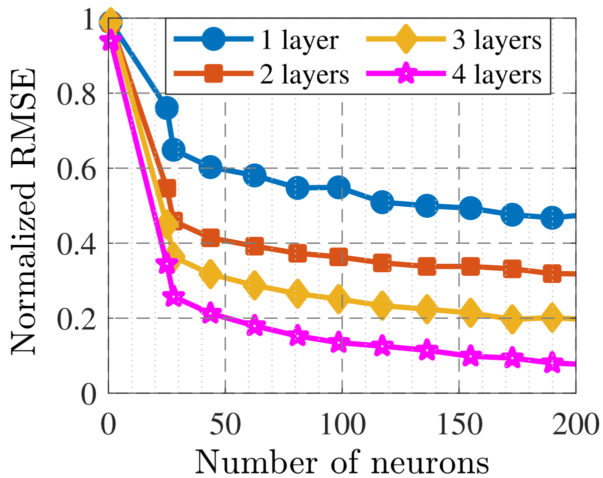

Fig. 3 Accuracy of the trained DNN at the fine modeling step.

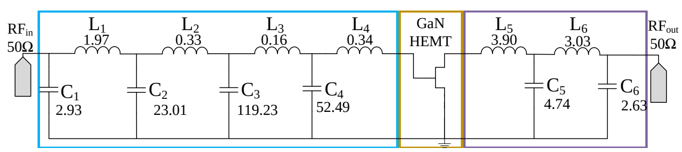

Fig. 4 Optimized PA with the executed GaN HEMT device; Unit of each capacitor and inductor are (pF) and (nH), respectively.

a thickness of 0.508 mm is used as a substrate and it is biased with a drain-source voltage of 50 V and quiescent drain-source current of 40 mA. With this constructed PA, 800 sequences include multi-segment S_{11}, S_{12}, and S_{22} specifications are generated for training the LSTM-based DNN as the coarse modeling step. In this stage, the hidden-layer configuration constructed from the fine modeling step is exactly substituted. This step leads to facilitating the sizing optimization of configured PA.

For the optimized PA operating from 1.7 GHz to 2.3 GHz, various results in terms of S-parameters and one-tone CW performances (i.e., P_{out}, G_P, and PAE at 3-dB gain compression) are performed. Figure 5 shows the detailed results for S_{11}, S_{22}, and S_{21} specifications. Here, the simulated S-parameters are compared with the estimated results with the help of trained DNN from 2.1 to 3 GHz. Additionally, one-tone CW performances are also presented in terms of simulated and predicted results in Figure 6. For the used HEMT device and the configured PA, a maximum PAE value of 60.2% with a linear G_p value larger than 11 dB at 40 dBm output power is achieved. It is observed that the predicted regions in both Figure 5 and Figure 6 are tracking the results achieved from simulations in an acceptable manner. The stability factor is well-enough in the whole bandwidth, which shows that the input and output matching networks are optimized in an improved way.

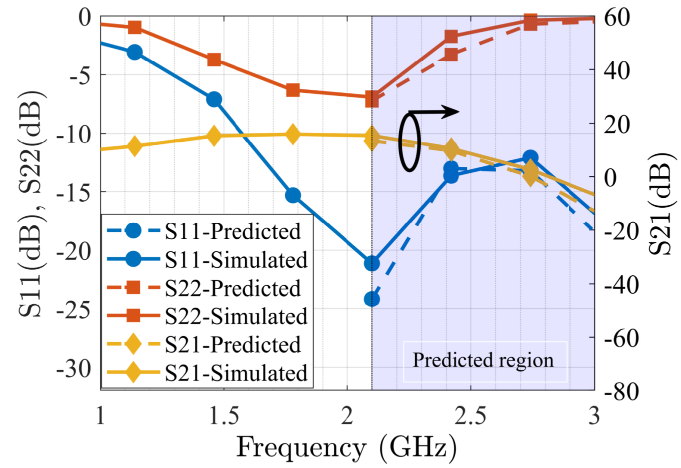

Fig. 5 S-parameter performances of the optimized PA.

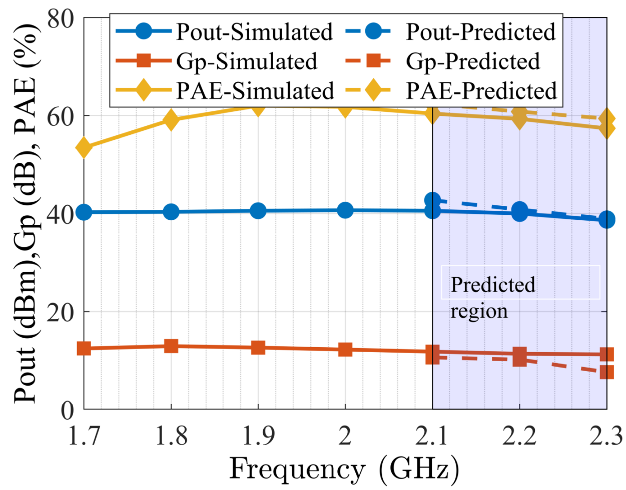

Fig. 6 P_{out}, G_p, and PAE results at 3-dB gain compression.

4 CONCLUSIONS

In this work, a DNN-based optimization method based on fine and coarse modeling is proposed. Firstly, the executed HEMT device is modeled through X-parameters, and then the S-parameters of PA are modeled through the configured DNN at the fine modeling stage. The presented procedure is effective enough since the hidden-layer configuration generated from fine modeling is employed for the DNNs at the coarse modeling stage and an NN is trained for sizing the PA. The fine and coarse modeling helps designers to configure the hidden layers of DNNs in a fast way without any need for optimization methods. The whole procedure is automated way, and a 10 W PA is designed and optimized to prove the effectiveness of the methodology operating from 1.7 GHz to 2.3 GHz.

AUTHOR CONTRIBUTIONS

Conceptualization, L.K. and M.A.; methodology, L.K, M.A., and S.O.; software, L.K.; validation, M.A., and S.O.; formal analysis, L.K.; investigation, M.A.; resources, S.O.; data curation, L.K.; writing—original draft preparation, L.K.; writing—review and editing, M.A., S.O; visualization, S.O.; supervision, S.O.; project administration, M.A. and S.O.; funding acquisition, S.O. All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] W. Li, H. Zeng, L. Huang, *et al.*, "A review of terahertz solid-state electronic/optoelectronic devices and communication systems," *Chinese Journal of Electronics*, vol. 34, no. 1, pp. 26–48, 2025. DOI: 10.23919/cje.2023.00.282.

[2] U. Ghafoor, "Strengthening data confidentiality in 6g cognitive networks through secrecy rate optimization," *IEEE Communications Letters*, pp. 1–1, 2025. DOI: 10.1109/LCOMM.2025.3537285.

[3] D. Zeng, H. Zhu, G. Shen, *et al.*, "A compact 24–30-ghz gan front-end module with coupled-resonator-based transmit/receive switch for 5g millimeter-wave applications," *IEEE Transactions on Microwave Theory and Techniques*, pp. 1–13, 2025. DOI: 10.1109/TMTT.2025.3530435.

[4] D. Wang, M. Aziz, M. Helaoui, and F. M. Ghannouchi, "Augmented real-valued time-delay neural network for compensation of distortions and impairments in wireless transmitters," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 1, pp. 242–254, 2019. DOI: 10.1109/TNNLS.2018.2838039.

[5] J. Wang, R. Su, J. Lv, G. Xu, and T. Liu, "Signal reconstruction deep residual neural network-based bandwidth augmented methods for dpd linearization," *IEEE Microwave and Wireless Technology Letters*, vol. 33, no. 3, pp. 243–246, 2023. DOI: 10.1109/LMWC.2022.3217691.

[6] Y. Wu, A. Li, M. Beikmirza, *et al.*, "Mp-dpd: Low-complexity mixed-precision neural networks for energy-efficient digital predistortion of wideband power amplifiers," *IEEE Microwave and Wireless Technology Letters*, vol. 34, no. 6, pp. 817–820, 2024. DOI: 10.1109/LMWT.2024.3386330.

[7] Z. Liu, X. Hu, L. Xu, W. Wang, and F. M. Ghannouchi, "Low computational complexity digital predistortion based on convolutional neural network for wideband power amplifiers," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 69, no. 3, pp. 1702–1706, 2022. DOI: 10.1109/TCSII.2021.3109973.

[8] S. Zhang, X. Hu, Z. Liu, *et al.*, "Deep neural network behavioral modeling based on transfer learning for broadband wireless power amplifier," *IEEE Microwave and Wireless Components Letters*, vol. 31, no. 7, pp. 917–920, 2021. DOI: 10.1109/LMWC.2021.3078459.

[9] A. Fischer-Bühner, L. Anttila, M. Turunen, M. Dev Gomony, and M. Valkama, "Augmented phase-normalized recurrent neural network for rf power amplifier linearization," *IEEE Transactions on Microwave Theory and Techniques*, vol. 73, no. 1, pp. 412–422, 2025. DOI: 10.1109/TMTT.2024.3484581.

[10] L. Kouhalvandi, O. Ceylan, and S. Ozoguz, "Automated deep neural learning-based optimization for high performance high power amplifier designs," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 67, no. 12, pp. 4420–4433, 2020. DOI: 10.1109/TCSI.2020.3008947.

[11] C. Belchior, L. C. Nunes, P. M. Cabral, and J. C. Pedro, "Towards the automated rf power amplifier design," in *2023 19th International Conference on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design (SMACD)*, 2023, pp. 1–4. DOI: 10.1109/SMACD58065.2023.10192148.

[12] L. Kouhalvandi and S. D. Guerrieri, "Modeling of hemt devices through neural networks: Headway for future remedies," in *2023 10th International Conference on Electrical and Electronics Engineering (ICEEE)*, 2023, pp. 261–267. DOI: 10.1109/ICEEE59925.2023.00054.

[13] L. Kouhalvandi and S. D. Guerrieri, "Nonlinear behavioral modeling of fets: Toward the implementation of deep neural networks through large signal data and eda tools," in *2024 19th European Microwave Integrated Circuits Conference (EuMIC)*, 2024, pp. 307–310. DOI: 10.23919/EuMIC61603.2024.10732844.

[14] P. Chen, J. Xia, B. M. Merrick, and T. J. Brazil, "Multi-objective bayesian optimization for active load modulation in a broadband 20-w gan doherty power amplifier design," *IEEE Transactions on Microwave Theory and Techniques*, vol. 65, no. 3, pp. 860–871, 2017. DOI: 10.1109/TMTT.2016.2636146.

[15] P. Chen, B. M. Merrick, and T. J. Brazil, "Bayesian optimization for broadband high-efficiency power amplifier designs," *IEEE Transactions on Microwave Theory and Techniques*, vol. 63, no. 12, pp. 4263–4272, 2015. DOI: 10.1109/TMTT.2015.2495360.

[16] *Ampleon*, https://www.ampleon.com/, Accessed: 2025-02-23.

[17] S. Yarman, "Design of ultra wideband power transfer networks," *New York, NY, USA: Wiley*, 2010. DOI: 10.1002/9780470688922.