An Extraction Method Based on Artificial Neural Network Techniques for Novel Cardiff Model with Reasonable Extrapolation Behavior

Mengyue Tian, James J. Bell, *Member, IEEE,* Roberto Quaglia, *Member, IEEE,* and Paul J. Tasker, *Fellow, IEEE*

***Abstract*—This letter presents an advanced Cardiff Model (CM) extraction method based on Artificial Neural Network (ANN) techniques that ensures reasonable extrapolation behavior. The non-physical extrapolation behavior occurring with CMs using a high, user-defined, mixing order, i.e., false output optima point and erroneous efficiency behavior, when extracted using measured load-pull datasets can be avoided with the proposed method. The method proposed maintains the accuracy within the load-pull measurements, design-relevant, impedance space. The method was verified by modelling the measured load-pull data of a Wolfspeed 10W Gallium Nitride (GaN) packaged device and a WIN Semiconductor GaN on-wafer device. With both devices, the extrapolation issues shown when using the high order CM are removed by the novel extracted CM coefficients.**

***Index Terms*—Behavioral models, load-pull measurement, Artificial Neural Network (ANN), nonlinear device modeling, Gallium Nitride (GaN) device.**

I. Introduction

THE A-B wave-based Cardiff Model (CM), as one of the polynomial mathematical formulated models, has been utilized reliably as a behavioral model for RF design [1]–[4]. With the appropriate user defined mixing order, it provides accurate interpolation predictions for measurement data. Generally, higher interpolation accuracy will require a higher user-defined mixing order. However, accurate extrapolation from the CM may require a low mixing order, truncation of the polynomial functions, or the need to use tailored datasets [5]. As a general rule-of-thumb *'high user-defined mixing order while improving interpolation is very likely to cause poor extrapolation results'* since the CM coefficient extraction is typically performed over a limited load-pull impedance range, due to both measurement system limitations and transistor operation constraints. This unfortunately may result in non-physical behavior during CM model use in CAD simulation, such as unrealistic optimum power and efficiency variations as a function of load, leading to the possibility for an optimizer to converge on non-physical solutions.

The A-B wave-based ANN behavioral models for RF transistors have also been proven to be a powerful tool for extracting the general relationships between the device input and output. With a proper model structure, analysis shows that ANN can also provide accurate predictions when moving out of the training data range [6]. Taking this extrapolation advantage into account, the proposed method in this paper involves a combination of a conventional A-B wave-based ANN model and the ANN-based Cardiff Model coefficients extractor [7] to provide novel sets of extracted high order CM coefficients that can offer both accurate interpolation and reasonable extrapolation behavior.

Two sets of data collected from load-pull measurements of two GaN devices, at different frequencies and power levels, will be used for both CM extrapolation problem detection and proposed method verification.

Manuscript received July 18, 2023. This work was supported in part by the Chinese Scholarship Council (CSC).*(Corresponding Author: Mengyue Tian)*

The authors are with the Center for High Frequency Engineering (CHFE), School of Engineering, Cardiff University, Cardiff, CF24 3AA (Email: mengyuet@cardiff.ac.uk).

II. Problem Detection

Active load-pull measurement systems were used for acquiring the design relevant measurement datasets. The Wolfspeed 10 W packaged device was measured (setup as in [8]) at 3.5 GHz, biased at V_{DS} = 28 V, I_{Dq} = 59 mA with a constant input drive corresponding to 1 dB compression at the optimum load. The WIN NP12 4x25 um on-wafer device was measured (setup as in [9]) at 20 GHz, biased at V_{DS} = 15 V, I_{Dq} = 10 mA with a constant input drive corresponding to 3 dB compression at the optimum load.

The coefficients of two 5^{th} order conventional CMs were extracted from the measurement dataset of the Wolfspeed and the WIN devices show, within the measured region, Normalized Mean Square Error (NMSE) levels of - 58 dB and - 52 dB for $B_{2,1}$ respectively. The extrapolation behavior of the conventional CM coefficients is then tested with manually generated stimulus $A_{2,1}$ circles, extending beyond the measurement area. To get the maximum coverage within the whole Smith Chart, a sweeping index c has been determined, from 1 to 6 for the Wolfspeed device, and from 1 to 5 for the WIN device for the circle propagation. The extrapolated load circles are markers and grayscale-coded consistently with c sweeps indexed as shown in Fig. 1.

Ideally, the CM computed (extrapolated) $B_{2,1}$ wave response as a function of the $A_{2,1}$ wave stimulus should show expanding circles/ellipses load points when moving away from the optimum. However, Fig. 1(a-b) shows clearly that this is not the case for the 5^{th} order CM, extrapolated results provide load points sitting on unrealistic trajectories with cusps and knots, as highlighted within the dash circles. This is because of the interaction between polynomial terms in the $B_{2,1}$ response yielding function limitations in the extrapolation region. This is best visualized in Fig. 1(c-d) where the extrapolated output

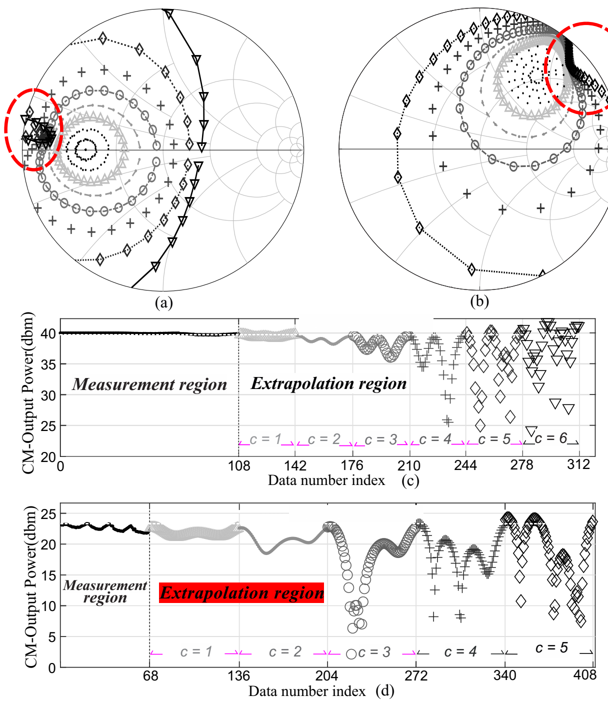

Fig. 1. The measured (black dots) and conventional CM extrapolated (grayscale-coded markers) load points on the Smith Chart; and output power levels for both the Wolfspeed device (a,c) and the WIN device (b,d).

power is not following a physically valid behavior, i.e., a decreasing trend away from the measured optimum, highlighted using different grayscale-coded markers for both devices. This may result in an optimizer converging on an erroneous load point when trying to optimize the matching networks.

III. Proposed Method

Previous work has shown that the accuracy of a Knowledge-Based Neural Network (KBNN) deteriorates slower than that of Multilayer Perceptions (MLPs) within the extrapolation region, since its knowledge layer allows built-in knowledge to give more information that is not seen in the training data [6]. This suggests that the KBNN model could be used to overcome the extrapolation issues shown for the conventional CM in section II. Also, an ANN-based CM coefficients extractor has been proven to output a set of coefficients with the same level of accuracy as the standard Least Mean Square (LMS) algorithm [7]. Therefore, a novel method is proposed in this paper, taking the advantages from the two model structures. An artificial set of extrapolated data outside the extraction region is generated with the KBNN model. The ANN model extractor will use the measured data in the feed-forward process, and the artificial data in the backpropagation, to achieve a new CM coefficient set that can provide reasonable extrapolation while maintaining the accuracy in the measurement region.

A. Step 1: Conventional ANN Setup

The Fully Connected Cascade (FCC) ANN model structure is selected as a simpler version of the KBNN model. As the first step, two FCC ANN models are implemented in a one-hidden-layer structure [6], [10] for both devices. The hidden

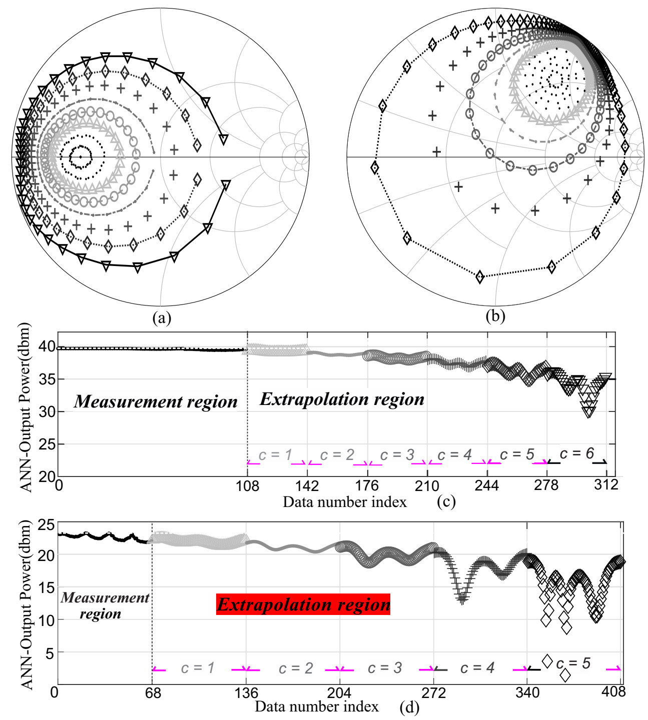

Fig. 2. The measured (black dots) and FCC ANN extrapolated (grayscale-coded markers) load points on the Smith Chart; and output power levels for both the Wolfspeed device (a,c) and the WIN device (b,d).

neuron numbers of the models are determined by an adaptive process [11], which results in 7 and 4 for the Wolfspeed and the WIN device respectively. The training is carried out with the measured A-B waves in Section II. Since the *tanh* function was selected as the activation function, note that measurement data will need to be normalized between -1 and 1 before feeding into the network training process. The scaling factor of the normalization process will need to be recorded for use in step 2. The NMSE levels provided within the measurement region of $B_{2,1}$ for the Wolfspeed and WIN devices are - 50 dB and - 45 dB, respectively.

B. Step 2: Conventional ANN Extrapolation

The trained A-B wave-based ANN models from step 1 can now be used for extrapolation. The scaling factor recorded from step 1, will be used to preprocess the $A_{2,1}$ wave for extrapolation that is generated in section II. This ensures that both the $A_{2,1}$ waves, that cover the expanded area on the Smith Chart and the measured $A_{2,1}$ waves, are kept within a meaningful boundary of the tanh function [10], [12] before being fed into the trained ANN.

The grayscale-coded markers in Fig. 2, clearly highlight that the extrapolation issue shown on the edge of the Smith Chart in Fig. 1(a-b) for both devices is absent in Fig. 2(a-b). Hence, the erroneous extrapolation behavior that can cause CAD simulation issues is absent. Now, the predicted output power levels of both devices are following a decreasing trend around the measured optimum as shown in Fig. 2(c-d). The extrapolated response provided by the trained FCC ANN models can now be used, in step 3, during CM coefficient extraction, to overcome the previously identified CM extrapolation issues.

C. Step 3: Extracting the CM coefficients with the ANN-based extractor

The trained ANN themselves could be used as reasonable extrapolation models. However, as a widely used commercially available behavioral model, the CM will provide a simpler polynomial structure and less calculation steps than those of the ANNs when the data complexity increases. Hence, an ANN-based Cardiff Model coefficients extractor [7] is now used. In this step, new CM coefficients sets are extracted using both the measured A-B wave dataset and the FCC ANN models (trained in step 2) predicted B wave dataset, instead of using measured data only. Since the ANN-based CM coefficient extractor is computing coefficients using both the measured data (over a limited impedance range over the Smith Chart) and the extrapolated data (over a significantly expanded range over the Smith Chart), the new extracted CM coefficient sets, even for high order Cardiff CAD models, should now provide for both accurate interpolation and reasonable extrapolation behavior. Details of the modified backpropagation Levenberg-Marquart Algorithm [7], [13] used for the ANN-based coefficient extractor is written as Algorithm 1.

Algorithm 1 Modified Steps of Levenberg-Marquart Algorithm for CM Coefficients Extractor

INPUT: $\boldsymbol{A}_{2,1\_Measured}$, $\boldsymbol{B}_{p,h\_Measured}$

$[\boldsymbol{A}] = (\angle\boldsymbol{A}_{1,1})^h \, |\boldsymbol{A}_{2,1\_Calculated}|^m \left(\frac{\angle\boldsymbol{A}_{2,1}}{\angle\boldsymbol{A}_{1,1}}\right)^n$

Initialization: $[\boldsymbol{W}_i], [\boldsymbol{B}_i] \leftarrow rand\,[-1, 1]$

for $epoch = 1$

$\boldsymbol{M}_{p,h,m,n} = [\boldsymbol{W}_i]\,[\boldsymbol{A}_{\mathbf{2,1}\_Measured}, \boldsymbol{B}_{p,h\_Measured}] + [\boldsymbol{B}_i]$

$\boldsymbol{B}_{p,h\_\mathbf{Modelled}} = \sum_{\mathbf{r}} \sum_{\mathbf{n}} \boldsymbol{M}_{p,h,m,n} \times [\boldsymbol{A}]$

$\boldsymbol{B}_{p,h\_\mathbf{Error}} = \boldsymbol{B}_{p,h\_\mathbf{Modelled}} - \boldsymbol{B}_{p,h\_ANNpredicted}$

$\boldsymbol{M}_{p,h,m,n\_Error} = \left([\boldsymbol{A}]^H [\boldsymbol{A}]\right)^{-\mathbf{1}} \left([\boldsymbol{A}]^H [\boldsymbol{B}_{p,h\_\mathbf{Error}}]\right)$

Compute ***Jacobian***

Initialization: $[\boldsymbol{W}_i]$ *and* $[\boldsymbol{B}_i]$ *till required error level met*

end for

OUTPUT: $\boldsymbol{M}_{p,h,m,n}$

where $[\mathbf{W_i}]$ and $[\mathbf{B_i}]$ represent the weight and bias matrices that are required in the ANN model structure, $M_{p,h,m,n}$ is the CM coefficients with 'p' and 'h' denoting the respective port, harmonic; 'r' is the magnitude indexing term; 'm' and 'n' are the magnitude and phase exponents related as $m = |n| + 2r$.

Here, with the measured and predicted datasets, the ANN-based CM coefficient extractors [7] are implemented under two-hidden-layer FCC structure, with hidden neuron numbers of each layer defined using an adaptive process [11]. For those of the Wolfspeed device, the hidden layers have 3 and 4 neurons respectively; and for the WIN device, both hidden layers have 5 neurons. The extracted CM coefficients in this case produce output power contours, shown in Fig. 3-4(a), absent are the unrealistic CAD simulation issues observed in Fig. 3-4(b). To obtain the efficiency contours, pure linear FCC ANN structures without any hidden layers are used for $I_{2,0}$ (drain DC current) extrapolation with the same process. The extreme, unrealistic, efficiency levels shown in Fig. 3-4(c) are also avoided by the CM coefficients extracted by the proposed new method as shown in Fig. 3-4(d).

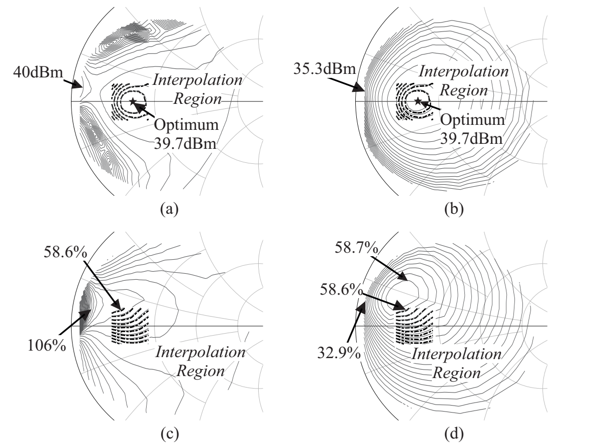

Fig. 3. Power and efficiency contours from the CM extracted using only measurement data (a, c), and the New Method (b, d), of the Wolfspeed device.

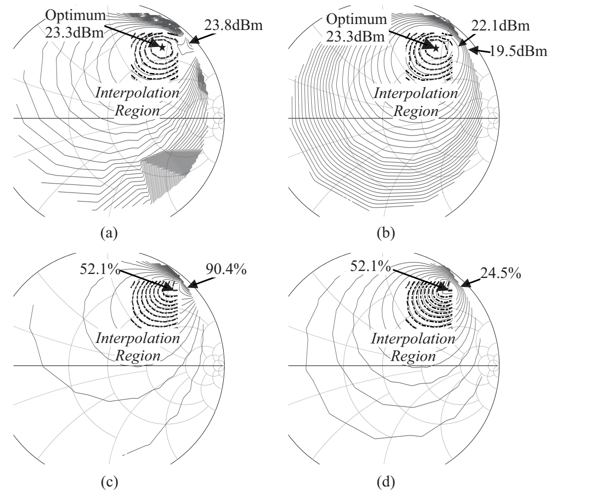

Fig. 4. Power and efficiency contours from the CM extracted using only measurement data (a, c), and the New Method (b, d), of the WIN device.

IV. Conclusion

This paper has introduced a novel procedure for extracting reasonable CM coefficients exploiting the superior extrapolation capabilities of Knowledge-Based Neural Network (KBNN) structure. Novel high mixing order CM coefficient sets were obtained, with the new method, providing accurate interpolation while also ensuring extrapolation without unrealistic power and efficiency predictions. The robustness of the novel proposed method is shown for two different GaN devices when using practical measured load-pull datasets under different frequency and power levels. The verification results show that the new method can help to avoid the non-physical CM model behavior when used in CAD simulations to optimize the matching networks, when CM model extraction is constrained by load-pull measurement limitations.

V. Acknowledgement

Thanks to WIN Semiconductors for the transistor samples.

REFERENCES

[1] H. Qi, J. Benedikt and P. J. Tasker, "Nonlinear Data Utilization: From Direct Data Lookup to Behavioral Modeling," in *IEEE Transactions on Microwave Theory and Techniques*, vol. 57, no. 6, pp. 1425–1432, June 2009, doi: 10.1109/TMTT.2009.2019996.

[2] P. J. Tasker and J. Benedikt, "Waveform Inspired Models and the Harmonic Balance Emulator," in *IEEE Microwave Magazine*, vol. 12, no. 2, pp. 38-54, April 2011, doi: 10.1109/MMM.2010.940101.

[3] J. Bell, "Input harmonic and mixing behavioral model analysis," Ph.D. dissertation, Dept. Electron. Eng., Cardiff Univ., Cardiff, U.K., 2014.

[4] M. R. Moure, M. Casbon, M. Fernández-Barciela and P. J. Tasker, "Direct extraction of an admittance domain behavioral model from large-signal load-pull measurements," *2017 IEEE MTT-S International Microwave Symposium (IMS)*, Honololu, HI, USA, 2017, pp. 1057-1060, doi: 10.1109/MWSYM.2017.8058775.

[5] P. J. Tasker, "Robust Extraction of Cardiff Model Parameters from Appropriately Tailored Measured Load-Pull Data," *2020 IEEE BiCMOS and Compound Semiconductor Integrated Circuits and Technology Symposium (BCICTS)*, Monterey, CA, USA, 2020, pp. 1-5, doi: 10.1109/BCICTS48439. 2020.9392942

[6] Q. -J. Zhang and K. C. Gupta, *Neural Networks for RF and Microwave Design.* Artech House, Boston, MS, USA, 2000.

[7] M. Tian, J. Bell, E. Azad, R. Quaglia and P. Tasker, "A Novel Cardiff Model Coefficients Extraction Process Based on Artificial Neural Network," *2023 IEEE Topical Conference on RF/Microwave Power Amplifiers for Radio and Wireless Applications*, Las Vegas, NV, USA, 2023, pp. 1-3, doi: 10.1109/PAWR56957.2023.10046221.

[8] R. Quaglia, D. J. Shepphard and S. Cripps, "A Reappraisal of Optimum Output Matching Conditions in Microwave Power Transistors," in *IEEE Transactions on Microwave Theory and Techniques*, vol. 65, no. 3, pp. 838-845, March 2017, doi: 10.1109/TMTT.2016.2627557.

[9] E. M. Azad, J. J. Bell, R. Quaglia, J. J. Moreno Rubio and P. J. Tasker, "Gate Bias Incorporation into Cardiff Behavioural Modelling Formulation," *2020 IEEE/MTT-S International Microwave Symposium (IMS)*, Los Angeles, CA, USA, 2020, pp. 420-423, doi: 10.1109/IMS30576.2020.9223817.

[10] D. Hunter, H. Yu, M. S. Pukish, III, J. Kolbusz and B. M. Wilamowski, "Selection of Proper Neural Network Sizes and Architectures—A Comparative Study," in *IEEE Transactions on Industrial Informatics*, vol. 8, no. 2, pp. 228-240, May 2012, doi: 10.1109/TII.2012.2187914

[11] V. K. Devabhaktuni, Changgeng Xi, Fang Wang and Qi-Jun Zhang, "Robust training of microwave neural models," *1999 IEEE MTT-S International Microwave Symposium Digest*, Anaheim, CA, USA, 1999, pp. 145-148 vol.1, doi: 10.1109/MWSYM.1999.779444.

[12] J. S. Smith, B. Wu, and B. M. Wilamowski, "Neural Network Training With Levenberg–Marquardt and Adaptable Weight Compression", *IEEE Transanctions on Neural Networks and Learning Systems*, vol. 30, no. 2, pp. 580–587, Feb. 2019, doi: 10.1109/TNNLS.2018.2846775.

[13] M. T. Hagan and M. B. Menhaj, "Training feedforward networks with the Marquardt algorithm," in *IEEE Transactions on Neural Networks*, vol. 5, no. 6, pp. 989-993, Nov. 1994, doi: 10.1109/72.329697.