Empowering the Bandwidth of Continuous Mode Symmetrical Doherty Amplifiers by Leveraging on Fuzzy Logic Techniques

Gideon Naah, Student Member, IEEE, and Rocco Giofrè, Senior Member, IEEE

Abstract—Achieving a fractional bandwidth (FBW) of more than 60% has been a challenging problem for two-way symmetrical Doherty power amplifiers (TW-SDPAs) that are designed using continuous mode technique. As reported in the literature, these designed continuous mode-based TW-SDPAs possess less than 52% FBW which cannot satisfactorily meet the challenging, complex and ever-evolving modulation schemes’ demands. To overcome such a limitation, this paper proposes a novel approach based on fuzzy logic techniques able to simplify and to speed up the design of continuous mode-based TW-SDPAs with state-of-art FBW. In particular, the proposed technique uses K-means unsupervised learning clustering algorithm and continuous mode technique in a modelled fuzzy logic system environment. As a result, extensive impedance solution design space is readily made available and the optimal impedances required by the carrier and peaking sub-amplifiers for efficiently operating at the saturation and output-power-back-off (OPBO) levels are automatically obtained. For verification, a TW-SDPA was designed and measured. According to the measured results, the TW-SDPA operates within 1.2–2.4 GHz frequency band, corresponding to 66.7% FBW. As compared to the designed continuous mode-based TW-SDPAs reported in the literature, this work indicates over 15% increment in FBW. Moreover, 41.59%–81.1% drain efficiency (DE) at saturation, 35%–63% DE at 6 dB OPBO, 42–45 dBm output power and 7–10.52 dB gain were successfully achieved. Adjacent channel leakage ratio (ACLR) better than –46 dBc and average DE within 46%–55% were successfully recorded after linearisation.

Index Terms—Continuous mode, Doherty power amplifiers (DPAs), fuzzy logic technique, fractional bandwidth (FBW).

I. INTRODUCTION

Due to the complex and ever-evolving nature of modulation schemes in wireless communication systems, power amplifiers (PAs) with large fractional bandwidth (FBW) and high-efficiency capabilities are in high demand. For that reason, radio frequency (RF) and microwave PA researchers have been pushed beyond the conventional limits and methods for designing PAs in order to meet the current and future needs. For instance, energy harvesting techniques have been introduced in PA designs in order to further improve the performance [1]–[3]. Furthermore, diverse fuzzy logic techniques such as interval type-2 fuzzy inference engine [4], self-organising fuzzy neural networks (SOFNNs) [5], radial-basis function neural networks (RBFNNs) [6], adaptive neuro-fuzzy inference system (ANFIS)-based Hammerstein [7], modified adaptive neuro-fuzzy inference system (MANFIS) [8] and many others [9]–[14] have been used by RF and microwave researchers to adequately solve the linearisation problems as well as reducing the power consumption level in PAs. Although the linearity performance in the reported amplifiers are substantially improved using these fuzzy logic techniques, the FBW performance of the amplifiers were not considered. The PAs were designed to function at single frequency points. This could be attributed to the motivation behind the designs and that is, enhancing the linearity performance in amplifiers.

Fifth-generation (5G) technology is the next-generation wireless technology being worked on by the industry and academia. It is expected to provide a data rate of 10-50 Gbps [16]. Despite its expected high functionalities, the large signal bandwidth required for high-speed data transmission is limited by the scarce spectrum resources. This therefore imposes stringent bandwidth requirements on the PAs.

Varieties of techniques and architectures that are based on the Doherty operating principle have been proposed for bandwidth extension [15]–[45]. Some of these techniques are the real frequency technique [21], Bayesian optimisation technique [31] and continuous mode technique [32–36]. Sun and Jansen [21] proposed the design of two-way symmetrical Doherty power amplifiers (TW-SDPAs) using real frequency technique. However, the recorded FBW is less than 30%. Similarly, Chen et al. [31] also proposed Bayesian optimisation for designing the TW-SDPAs. Nevertheless, the measured FBW is less than 47%. In the case of the continuous mode TW-SDPAs proposed by Chen et al. [32–34] and Shi et al. [35–36], the reported bandwidths are also less than 52% even if the beneficial effect of the continuous mode technique on the efficiency figure was tangible. Giofrè et al. [40], Yang et al. [42] and Rubio et al. [43] proposed TW-SDPAs that were not accomplished using continuous mode technique. Upon comparing [40], [42] and [43] with [32–36], this is a clear indication that the reported continuous mode-based TW-SDPAs are critically facing bandwidth problems. As a result, cannot meet the challenging demands and the successful deployment of modern wireless communication systems. In summary, none of the continuous mode TW-SDPA designs reported in the literature have considered a modelled fuzzy...
logic and continuous mode techniques with $K$-means unsupervised learning clustering algorithm for solving the bandwidth problem in the continuous mode TW-SDPAs.

To address the bandwidth limitations in the continuous mode-based TW-SDPAs, a continuous fuzzy logic mode technique (CFLMT) is proposed in this paper. The proposed technique uses a modelled $K$-means unsupervised learning clustering algorithm and a modelled continuous mode technique in a modelled fuzzy logic system environment which can extend the bandwidth of the TW-SDPA. To extend the bandwidth of the TW-SDPA, the proposed methodology directly solves for the TW-SDPA design parameters in two separate sub-clustered regions. The optimal impedances required by the carrier and peaking sub-amplifiers for efficiently operating at the saturation and output-power-back-off (OPBO) levels are automatically obtained. Even though the major target in this paper is to solve the bandwidth problem in the continuous mode-based TW-SDPAs, substantial performance indicators such as efficiency, output power, and gain were not ignored. For validating the proposed technique, a 1.2–2.4 GHz TW-SDPA with 66.7% FBW was designed, implemented and measured. Upon comparing the FBW performance of the proposed TW-SDPA to that reported by Chen et al. [32–34] and Shi et al. [35–36], 15.5%–29.7% increment in FBW is successfully demonstrated by the proposed TW-SDPA in this work.

The residue of this paper is organised as follows: Section II presents the analysis of the proposed TW-SDPA concept. Section III gives the design approach for the proposed broadband TW-SDPA. Measurement results under different excitations of the carriers and peaking branches at the combining node can be expressed as

$$Z_C \text{OPBO} = \frac{Z_L}{1 + \frac{I_{P\text{Sat}}}{I_{C\text{Sat}}}}$$
$$Z_C \text{Sat} = \frac{Z_L}{1 + \frac{I_{P\text{Sat}}}{I_{C\text{Sat}}}}$$

(1)

$$Z_P \text{OPBO} = \frac{I_{C\text{Sat}}}{I_{P\text{Sat}}} Z_L$$
$$Z_P \text{Sat} = \frac{I_{C\text{Sat}}}{I_{P\text{Sat}}} Z_L$$

(2)

where $Z_C\text{Sat}$ and $Z_P\text{Sat}$ represent the load impedances, at the device output, of the carrier and peaking amplifiers while $I_C$ and $I_P$ are the correspondent currents, respectively. $Z_0$ designates the characteristic impedance of the impedance inverting network (IIN). The TW-SDPA consists of a carrier PA and a peaking PA for which they are independently biased in class-B and class-C, respectively. These two sub-amplifiers are combined by a two-section Wilkinson power divider at the input and connected to a common load $Z_L$ at the output. A post-matching network (PMN) is therefore constructed for matching the standard 50 $\Omega$ to $Z_L$ at the combining node. The PMN provides an appropriate fundamental load termination. The architecture is then completed with the phase compensation line (PCL). Targets 1–5 in Fig. 1(c) indicate the levels of priorities assigned to the expected performance indicators from the TW-SDPA to be designed. Target 1 indicates the topmost prioritised goal followed by Target 2 being the second most prioritised goal. Then to the third, fourth and finally, to the fifth prioritised goal. Clearly, both the targets and their order are not fixed and can be chosen in accordance with the designer needs.

According to the existing TW-SDPA concept on active load modulation, the effective load impedances of the carrier and peaking branches at the combining node can be expressed as

$$\nu_{ds}(t) = (1 - (\alpha \cos(\omega t) - \delta \cos(3\omega t))\beta)(1 - \gamma \sin(\omega t))$$

(3)
where \( \alpha, \beta, \delta \) and \( \gamma \) designate the continuous fuzzy logic mode parameters to be used in obtaining the optimum characteristic impedances and electrical lengths of the transmission lines in the TW-SDPA, and load impedances required by the carrier and peaking devices for efficiently operating at the saturation and OPBO levels. To effectively characterise the CFLMT operating conditions, the \( \gamma \) parameter has been specified to function within 0 and 1, i.e. \( 0 \leq \gamma \leq 1 \). This differs from the conventional continuous mode operation condition where \( \gamma \) ranges from -1 to 1, i.e. \( -1 \leq \gamma \leq 1 \). The reason for specifying the \( \gamma \) parameter to function within 0 and 1 is to satisfy the membership function conditions in the fuzzy logic system as proposed by Zadeh [47].

A. Modelling of the Continuous Fuzzy Logic Mode Membership Functions

Shown in Fig. 2 is the continuous fuzzy logic mode membership functions under normalised conditions. Supposing that there exists a universe of discourse \( Z \) and its elements are designated by \( \delta, \alpha \) and \( \beta \), then a fuzzy set \( \tilde{z} \) in \( Z \) can be expressed as

\[
\tilde{z} = \{ (\alpha, \beta, \delta), \mu_{\tilde{z}}(\alpha, \beta, \delta) | (\alpha, \beta, \delta) \in Z \}
\]

where \( \mu_{\tilde{z}}(\delta), \mu_{\tilde{z}}(\alpha) \) and \( \mu_{\tilde{z}}(\beta) \) are defined as the membership functions (see Figs. 2(a)–(c)). Collectively, the membership functions can be defined as \( \mu_{\tilde{z}}(\alpha, \beta, \delta) \) (see Fig. 2(d)). The CFLMT proposed in this work uses \( K \)-means unsupervised learning clustering algorithm. For that matter, data nodes are needed in the training. As clearly demonstrated in Fig. 2, within each sub-figure lies a set of nodes for which will help determine the suitable impedances and electrical lengths for designing the TW-SDPA. In Fig. 2(d), \( R_1, R_2 \) and \( R_3 \), respectively, signify regions 1, 2 and 3. By unifying Fig. 2(a), Fig. 2(b) and Fig. 2(c), Fig. 2(d) is obtained as a consequence. Since each sub-figure contains training data nodes, it will be appropriate to present them in a unified setting, then find the optimum nodes within each region. As illustrated in Figs. 2(a)–(c), the nodes in Fig. 2(a) cannot be found in Figs. 2(b) and (c), and vice versa. However, in Fig. 2(d), all the training nodes can be found in \( R_1 \sim R_3 \). By this approach, a reduced number of fuzzy rules and parameters can be guaranteed and as a consequence, can lead to obtaining better convergence solutions. Furthermore, the time-wasting search carried out by most algorithms, which even leads to convergence problems, can be avoided.

In reference to Fig. 2(d), by applying fuzzy sets theory, the \( \alpha, \delta \) and \( \beta \) parameters are bounded to function within \( 0 \leq \alpha \leq 1, 0 \leq \delta \leq 1 \) and \( 0 \leq \beta \leq 0.5 \), respectively. The constraint placed on the \( \beta \) parameter clearly indicates that even though it influences the \( \alpha \) and \( \delta \) parameters, the highest priorities are placed on the \( \alpha \) and \( \delta \) parameters. This is because, the \( \alpha \) and \( \delta \) parameters strongly determine and guarantee the CFLMT operating conditions. Moreover, considering Fig. 2(d), the optimal training nodes associated to the \( \alpha, \delta \) and \( \beta \) parameters to be determined in \( R_1 \sim R_3 \), can be specified in a data solution space for which it is defined as continuous fuzzy mode solution space (CFMSS). In order to determine the CFMSS in \( R_1 \) where the optimal training nodes associated to the \( \alpha \) and \( \delta \) parameters can be found, the relation below can be applied

\[
CFMSS_{R1} = jR_1 \int_{z_0, x=0.73}^{z_0, y=1} \alpha_1(\tilde{z}) \delta_1(\tilde{z}) \ d\tilde{z}
\]
where \( j \) denotes the total number of nodes, i.e., \( j \) in R1, \( i = 1, 2, 3, \ldots, nth \), and \( \gamma_{0,x} \) and \( \gamma_{0,y} \), respectively, designate the lower and upper limit membership function boundary conditions for \( \alpha \) and \( \delta \) in R1. Similarly, to determine the CFMSS in R2 and R3, the relations below can be applied

\[
CFMSS_{R2} = kR2 \int_{\gamma_{1,y}=0.73}^{\gamma_{1,y}=0.73} \alpha_i(\bar{z}) \delta_i(\bar{z}) \beta_i(\bar{z}) \, d\bar{z}
\]

\[
CFMSS_{R3} = lR3 \int_{\gamma_{2,x}=0}^{\gamma_{2,x}=0} \delta_i(\bar{z}) \beta_i(\bar{z}) \, d\bar{z}
\]

where \( kR2 \) and \( lR3 \) indicate the total number of nodes, i.e., \( k \) and \( l \) in R2 and R3, respectively, \( i = 1, 2, 3, \ldots, nth \), \( \gamma_{1,y} \), and \( \gamma_{2,x} \) and \( \gamma_{2,y} \), respectively, designate the lower and upper limit membership function boundary conditions for \( \alpha \), \( \delta \) and \( \beta \) parameters in R2, and \( \delta \) and \( \beta \) parameters in R3. With the introduced \( \gamma_{0}, \gamma_{1,y} \) and \( \gamma_{2,x} \) lower and upper limit membership functions boundary conditions in R1, R2 and R3, respectively, the effect of high levels of uncertainties in the CFLMT can be better handled and minimised. By taking into consideration R1, R2 and R3, the overall CFMSS can be expressed as

\[
CFMSS_T = jR1 \int_{\gamma_{0,x}=0.73}^{\gamma_{0,x}=0.73} \alpha_i(\bar{z}) \delta_i(\bar{z}) \, d\bar{z}
\]

Appropriate load modulating conditions in (1)–(2) for the conventional continuous mode-based TW-SDPAs cannot be exactly accomplished over a continuous frequency range due to the well-known matching limitations [48]. Therefore, by introducing (8) in (1) and (2), the CFLMT may find the optimum impedances required by the carrier and seeking sub-amplifiers for effective load matching and load modulating conditions at both saturation and OPBO levels, as a consequence, providing bandwidth extension and high-efficiency enhancement. That said, the relations for (1) and (2) may be, respectively, redefined as follows after some rearrangement

\[
Z_{\text{CFM}} = Z_\text{R} \left( \alpha \delta + \alpha \left( \frac{1 + \beta}{2} \right) - \beta \gamma \right)
\]

\[
Z_{CFM1} = Z_\text{R} \left( \alpha \delta + \alpha \left( \frac{1 + \beta}{2} \right) - \beta \gamma \right)
\]

\[
Z_{CFM2} = Z_\text{R} + \left( \alpha \delta \left( - \left( \frac{1 - \beta}{2} \right) \frac{3\pi}{8} \right) \right)
\]

\[
Z_{CFM3} = \infty
\]

B. Modelling of the Continuous Fuzzy Mode Impedance Solution Design Space

Supposing that the fundamental \((Z_{CFM1})\) and second \((Z_{CFM2})\) harmonic impedance domain relating to the continuous fuzzy logic mode from which the suitable OPBO and saturation impedances, characteristic impedance and electrical length of each transmission line of the TW-SDPA may be obtained, \(Z_{CFM1}\) and \(Z_{CFM2}\) are, respectively, expressed as

\[
Z_{CFM1} = Z_\text{R} \left( \alpha \delta + \alpha \left( \frac{1 + \beta}{2} \right) - \beta \gamma \right)
\]

\[
Z_{CFM2} = Z_\text{R} + \left( \alpha \delta \left( - \left( \frac{1 - \beta}{2} \right) \frac{3\pi}{8} \right) \right)
\]

\[
Z_{CFM3} = \infty
\]

C. Modelling of the K-Means Unsupervised Learning Clustering Algorithm for the Continuous Fuzzy Mode Impedance Solution Design Space

First and foremost, it is essential to note that most algorithms used in the TW-SDPA designs do function with high number of variables, rules and techniques. By these approaches, it is very difficult to tell which variable belongs to which sub-amplifier for saturation and OPBO operations. In order to solve this kind of problem and to make the design process more easier for the RF/microwave PA designer, the proposed technique rather feeds in the modelled CFM equations into the proposed system. It is evident that the number of variables in the modelled CFM equations are two to be precise, thus \( \alpha \) and \( \delta \). Only that the influence of the \( \beta \) variable is considered which makes it appear to have only three variables in all. Moreover, for each modelled CFM equation, one can easily determine the required optimal variables with their associated impedance values belonging to each sub-amplifier for saturation and OPBO operations.

In the K-means unsupervised learning clustering algorithm, there are four \( K \) clusters in all which are associated to the performance indicators with the five targets shown in Fig. 1(c). Each K cluster possesses two sub-clusters labelled as R1 and R2. More than 700 training nodes are assigned to each sub-cluster. Moreover, no initial guesses are required [31]. Furthermore, according to the continuous mode operation technique, the third harmonic impedance, thus \( Z_{CFM3} \) must be equated to \( \infty \). For that matter, \( Z_{CFM3} \) is void of training parameters.
nodes. This is done to ensure the continuous mode operation condition is satisfied. Also, in order to easily identify the $\alpha$ and $\delta$ variables in $R_1$ and $R_2$, and to lesson computational complexity as well as increase the possibility of finding the optimal convergence solution in the $K$-means algorithm, $\alpha$ is assigned to $R_1$ while $\delta$ is assigned to $R_2$. Before the formation of each cluster, a centroid also known as mean is selected from the training nodes in each region. The selected centroids move around and the minimum distance between the chosen centroids and other training nodes are calculated. The node with the minimum distance is selected as the new centroid. This process continuous until the cluster centroids stop changing their positions and become static. Once the clusters become static, the $K$-means clustering algorithm is said to have converged. Finally, the $K$-means clustering algorithm divides the training nodes into four major clusters with each cluster having two sub-clusters. The objective functions for the $K$-means algorithm are as follows

$$F_{obj,1} = \sum_{i=1}^{mR_1} \sum_{j=1}^{nR_2} \left( Z_{C@OPBO} - \mu_{z(\alpha_i, \delta_i)} Z_{opt} \right)$$  \hspace{1cm} (12)$$

$$F_{obj,2} = \sum_{i=1}^{mR_1} \sum_{j=1}^{nR_2} \left( Z_{C@Sat} - \mu_{z(\alpha_i, \delta_i)} Z_{opt} \right)$$  \hspace{1cm} (13)$$

$$F_{obj,3} = \sum_{i=1}^{mR_1} \sum_{j=1}^{nR_2} \left( Z_{P@Sat} - \mu_{z(\alpha_i, \delta_i)} Z_{opt} \right)$$  \hspace{1cm} (14)$$

where $mR_1$ and $nR_2$ designate the total number of selected optimal nodes, i.e. $m$ and $n$ in $R_1$ and $R_2$, respectively, from $K_1 \sim K_4$ clusters, and $Z_{opt}$ is the optimal impedance required by a class-B biased CGH40010F transistor. The fuzzy logic system environment suitable for the effective execution of the $K$-means algorithm comprises three main parts which are (a) fuzzification, (b) fuzzy inference engine with fuzzy rule base and (c) defuzzification. At the fuzzification stage, the modelled CFM equations supplied to the fuzzy system are converted to a suitable form ready for processing. The converted CFM equations are then processed by the fuzzy inference engine. However, the fuzzy inference engine operates strictly based on the fuzzy rules located in the fuzzy rule base. As a matter of fact, the fuzzy rules greatly impact the output to be generated at the defuzzification stage. The defuzzification stage processes the final output. The fuzzy rules employed
in the algorithm are based on IF-THEN rules and are shown below

**Rule 1:** IF $\alpha_i$ in $R1$ is $\mu_{\alpha_i}(z)$, THEN $G = \int_{\alpha_i(z)}^{\delta_i(z)} d\beta$

**Rule 2:** IF $\delta_i$ in $R2$ is $\mu_{\delta_i}(\tilde{z})$, THEN $H = \int_{\delta_i(\tilde{z})}^{\gamma_i(\tilde{z})} d\tilde{\beta}$

where $G$ and $H$ are defined as the consequent parameters, in other words output parameters of the fuzzy system.

After convergence, the optimal $\alpha$ and $\delta$ variables in $R1$ and $R2$, respectively, are selected from each $K$ cluster. Otherwise, the fuzzy rules are modified and the process is repeated. The chosen optimal variables associated to each sub-amplifier at both saturation and OPBO operations are then used in designing the TW-SDPA. The performance indicators of the designed TW-SDPA are then verified by simulation in Keysight’s Advanced Design System (ADS).

As observed from the $K$-means algorithm, the reduced number of fuzzy rules and parameters may lead to the acquisition of better convergence results. With the CFM technique, the solution space is narrowed to $R1$ and $R2$ within the Smith chart. As a result, the time required to find the optimum parameters for the TW-SDPA design is much smaller as compared to the time required in finding the optimum parameters in the entire regions in the Smith chart. Fig. 3 shows the obtained $K$-means clusters. It is to be noted that $Z_{\text{CFM1}}$, $Z_{\text{CFM2}}$ and $Z_{\text{CFM3}}$ in (11a), (11b) and (11c) are assigned to $R1$, $R2$ and $R3$, respectively, in each cluster.

Finally, after determining the optimal $\alpha$ and $\delta$ parameters in $R1$ and $R2$, respectively, in each $K$ cluster, they are then assigned to their associated impedances of the carrier and peaking sub-amplifiers. In other words, the chosen optimal $\alpha$ and $\delta$ parameters in each sub-cluster are assigned to $Z_{\text{CFM}}$, $Z_{\text{CBS}}$ and $Z_{\text{PAS}}$ for effective load matching and load modulating operation at both saturation and OPBO as shown in Fig. 3. (In the case of determining the characteristic impedances ($Z_\alpha$) and electrical lengths ($\theta_\alpha$) of the transmission lines of the TW-SDPA, similar procedure is used. However the chosen optimal $\alpha$ and $\delta$ parameters are assigned to $Z_{\text{CFM}}$, $Z_{\text{CBS}}$ and $Z_{\text{PAS}}$ in each region. This assignment process uses a modelled fuzzy logic $\text{max}$ operator for the $\alpha$ and $\delta$ parameters for which will be explained in details in Section III. Moreover, it is obvious this design approach not only includes efficiency and output power performance indicators with their associated harmonic load impedances at the initial design stage. Additionally, gain and bandwidth performance indicators are also considered.

### III. Proposed Broadband Two-Way Symmetrical DPA Design and Simulation

To commence with the derivation of the actual impedances to be used in designing the TW-SDPA prototype, it is befitting to introduce its design requirements, complete block diagram and complete schematic as shown in Table I, Fig. 4 and Fig. 5, respectively. The design employs two Wolfspeed’s CGH40010F gallium nitride (GaN) packaged transistors. The carrier and peaking devices possess a single drain bias voltage supply for which it is set to 28 V while the carrier and peaking gate bias voltages are set to $-2.7$ V and $-5.8$ V, respectively.

The theory presented in the previous section will be applied to design the TW-SDPA with extended bandwidth and high-efficiency operation in this section. That said, it is vital to firstly present the practical DPA circuit design guidelines before giving a demonstration, which are given as follows.

A fuzzy DPA topology with its associated OMNs, input matching networks (IMNs), gate and drain biasing networks, IIN and PMN must firstly be chosen by the designer. Equal number of training data nodes must be set for each sub-cluster. With the fuzzy rules and (12-14) in place, $G = \alpha$ and $H = \delta$ (where $\alpha$ and $\delta$ signify the optimal parameters to be obtained from the sub-clusters at the defuzzification stage. With (12-14), the degree of mismatch within the chosen fuzzy DPA topology can be minimised. Moreover, acquiring better convergence solutions can be made possible. This can lead to better transition from the fuzzy DPA topology to the actual DPA topology realisation. Then, execute the proposed algorithm in order to obtain the optimal $\alpha$ and $\delta$ parameters from each $K$ cluster. After convergence, from (11a)-(11b), (9) and (10) relating to the carrier and peaking PAs, respectively, are firstly determined.

Next, to determine the characteristic impedance and electrical length for all the transmission lines in each chosen network such as OMN, first replace (9) and (10) in (11) with $Z_{\alpha}$ and $\theta_{\alpha}$ where $\alpha = 1, 2, 3$. Furthermore, to use $Z_{\alpha}$ and $\theta_{\alpha}$ in the objective functions $Z_\alpha$ replaces $Z_{\text{Sat}}$ in (13) while $\theta_{\alpha}$ replaces $Z_{\text{OPBO}}$ in (14). For $\theta_{\alpha}$ in (14), $\theta_{\text{opt}}$ is replaced by $\theta_{\text{opt}}$ where $\theta_{\text{opt}}$ defines the optimum electrical length of the transmission lines. Execute the algorithm once again to obtain the optimal $\alpha$ and $\delta$ parameters from each $K$ cluster after convergence. That means, to determine the optimal $\alpha$ and $\delta$
parameters for each chosen network, the algorithm must be executed time.

Next, use the modelled fuzzy logic max operators shown in (15) and (16) to finally obtain the actual load impedances, i.e. (9) and (10) of the carrier and peaking PAs, respectively, as well as the actual characteristic impedance and electrical length for all the transmission lines in each chosen network. Hence, it is through (15) and (16) that the actual DPA impedance and electrical length design values are acquired.

Therefore, in order for the proposed theory to be effective in design, the modelled fuzzy logic max operators pertaining to the $\alpha$ and $\delta$ parameters can be, respectively, expressed as

$$\sum_{i=1}^{mR1} \max(\alpha_0, \alpha_1, ..., \alpha_p)mR1$$  \hspace{1cm} (15)$$

$$\sum_{j=1}^{nR2} \max(\delta_0, \delta_1, ..., \delta_q)nR2.$$  \hspace{1cm} (16)

In addition, the fuzzy logic max operators perform the following tasks: (a) make a comparison of the optimal parameters obtained in one region and then select the most suitable and maximum parameter, (b) make a comparison of the optimal parameters obtained across the regions and then finally select the maximum parameter suitable for designing the TW-SDPA, and (c) account for the impact of the other parameters on the selected ones. The physical application of (15) and (16) in the acquisition of the load impedances of the carrier and peaking sub-ampifiers are demonstrated as follows. In reference to Table II, it is worth noting that there exist $\alpha_0$ to $\alpha_{11}$ node parameters relating to $mR1$ in (15). Similarly, there exist $\delta_0$ to $\delta_{11}$ node parameters relating to $nR2$ in (16). As a reminder, $mR1$ and $nR2$ designate the total number of selected (optimal) nodes, i.e. $m$ and $n$ in $R1$ and $R2$, respectively, from $K_1 \sim K_4$ clusters after convergence. Clearly, $mR1$ has 12 $\alpha$ node parameters, i.e. $\alpha_0$ to $\alpha_{11}$. Likewise, $nR2$ has 12 $\delta$ node parameters, i.e. $\delta_0$ to $\delta_{11}$. From Table II, the selected optimal $\alpha$ values in $R1$ from $K_1 \sim K_4$ clusters are $\alpha_0 = 0.5$,
The next step is the acquisition of the suitable characteristic impedance and electrical length of each transmission line in each network of the DPA. To achieve this, $Z_{CBO}$ and $Z_{PBO}$ where $\theta = 1, 2, 3, \ldots$ are introduced in (11) to replace (9) and (10). In obtaining the actual impedance and electrical
length values for each network using (15) and (16), the procedure used in acquiring $Z_{CBO\text{OPBO}}$ is applied. As an example, with reference to Table III, to determine the actual $\alpha$ and $\delta$ values in $Z\theta$ and $Z\delta$ for $Z_{\text{IM}}$ are $\alpha = 0.01$, $\delta = 0.03$, $\theta = 0.1153$, $\delta = 0.05$, and $\gamma = 0.04$, $\delta = 0.081$, $\theta = 0.053$, respectively. Using (15) and (16), $\max(\theta) = 0.01$, $\delta = 0.03$, $\gamma = 0.1153$, $\theta = 0.0512$ and $\max(\alpha) = 0.07$, $\delta = 0.09$, $\theta = 0.0817$, $\alpha = 0.053$, respectively. Then, $0.1153 \times 0.01 \times 3.84 \Omega$ is obtained using (15) while $0.09 \times 0.07 \times 3.84 \Omega$ is obtained using (16). Next, $\max(1.384, 1.0824)$ makes $Z_{\text{IM}}$ (1.384) $= 33.29 \Omega$. Likewise, for $Z_{\text{ON}}$, we have $0.02$, $\alpha = 0.001$, $\theta = 0.0255$, $\alpha = 0.01$, and $\theta = 0.0328$, $\alpha = 0.053$, $\theta = 0.0009$. Using (15) and (16), $\max(\alpha) = 0.03$, $\delta = 0.01$, $\alpha = 0.0255$, $\theta = 0.01612$, and $\max(\theta) = 0.0328$, $\gamma = 0.03$, $\alpha = 0.053$, $\theta = 0.0009$), respectively. Then using (15) $0.0255 \times 0.01 \times 3.84 \Omega$ (while using (16) $0.0328 \times 0.02 \times 3.84 \Omega$). Next, $\max(0.306, 0.3936) = 0.3936$, and $\theta = 0.3936 \times 2 \approx 0.986$. The characteristic impedances and electrical lengths were not strictly bounded. This is because, every node in each cluster possesses possibilities and potentials of donating the right impedance and electrical length to the microstrip lines for bandwidth extension. In the execution of the $K$-means clustering algorithm, the number of iterations is set to about 14. After the 14th iteration, each cluster remained static as well as the obtained $\alpha$ and $\delta$ values. This indicates the algorithm has converged and suitable solutions are found.

In summary, one can easily observe that for each $\alpha$ and $\delta$ parameter in each region, there exist one $Z_{CBO\text{OPBO}}$, $Z_{CBO\text{Sat}}$, $Z_{P\text{PA\text{Sat}}}$, $Z_{\text{ON}}$, and $\theta_{\alpha}$. With (15) and (16), comparisons are made in order to still find the optimal $Z_{CBO\text{OPBO}}$, $Z_{CBO\text{Sat}}$, $Z_{P\text{PA\text{Sat}}}$, $Z_{\text{ON}}$, and $\theta_{\alpha}$. In other words, for each $Z_{CBO\text{OPBO}}$ obtained from the $\alpha$ and $\delta$ parameters in each region, (15) and (16) do function to select the optimal $Z_{CBO\text{OPBO}}$ value suitable for designing the TW-SDPA. Likewise, the same process is carried out for $Z_{CBO\text{Sat}}$, $Z_{P\text{PA\text{Sat}}}$, $Z_{\text{ON}}$, and $\theta_{\alpha}$ in order to find the optimal values. By using (15) and (16) the actual impedance and electrical length design values obtained for the microstrip lines in the IMNs, OMNs, gate and drain biasing networks, IIN and PMN are shown in Table IV. The residue of the design details are given as follows.

The designed OMN and drain biasing network of the carrier amplifier are displayed in Fig. 6. Moreover, the device package of the CGH40010F transistor is included in the design as shown in the figure. The impedance trajectories of the accomplished carrier device OMN and drain biasing network are demonstrated at OPBO and saturation as shown in Fig. 7. As observed in Fig. 7, the TW-SDPA is capable of providing

<table>
<thead>
<tr>
<th>Carrier-Amplifier Impedance and Electrical Length Design Values</th>
<th>Drain Biasing Network</th>
<th>Gate Biasing Network</th>
<th>OMN</th>
<th>OMN</th>
<th>IMN</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z_{\theta}$ = 50.12 $\Omega$ ($\theta = 13.5^\circ$)</td>
<td>$Z_{\theta}$ = 68.66 $\Omega$ ($\theta = 18.6^\circ$)</td>
<td>$Z_{\theta}$ = 68.66 $\Omega$ ($\theta = 3.73^\circ$)</td>
<td>$Z_{\theta}$ = 33.22 $\Omega$ ($\theta = 9.45^\circ$)</td>
<td>$Z_{\theta}$ = 33.22 $\Omega$ ($\theta = 31.1^\circ$)</td>
<td>$Z_{\theta}$ = 33.22 $\Omega$ ($\theta = 1.97^\circ$)</td>
</tr>
<tr>
<td>$Z_{\delta}$ = 25.9 $\Omega$ ($\delta = 28.9^\circ$)</td>
<td>$Z_{\delta}$ = 68.66 $\Omega$ ($\delta = 18.6^\circ$)</td>
<td>$Z_{\delta}$ = 68.66 $\Omega$ ($\delta = 8.2^\circ$)</td>
<td>$Z_{\delta}$ = 33.22 $\Omega$ ($\delta = 28.9^\circ$)</td>
<td>$Z_{\delta}$ = 33.22 $\Omega$ ($\delta = 28.9^\circ$)</td>
<td>$Z_{\delta}$ = 33.22 $\Omega$ ($\delta = 18.6^\circ$)</td>
</tr>
<tr>
<td>$Z_{\theta}$ = 33.212 $\Omega$ ($\theta = 7.87^\circ$)</td>
<td>$Z_{\theta}$ = 66.68 $\Omega$ ($\theta = 52.19^\circ$)</td>
<td>$Z_{\theta}$ = 66.68 $\Omega$ ($\theta = 14.54^\circ$)</td>
<td>$Z_{\theta}$ = 52.17 $\Omega$ ($\theta = 24^\circ$)</td>
<td>$Z_{\theta}$ = 52.17 $\Omega$ ($\theta = 20.2^\circ$)</td>
<td>$Z_{\theta}$ = 52.17 $\Omega$ ($\theta = 20.2^\circ$)</td>
</tr>
<tr>
<td>$Z_{\delta}$ = 12.18 $\Omega$ ($\delta = 48.16^\circ$)</td>
<td>$Z_{\delta}$ = 50.12 $\Omega$ ($\delta = 17.5^\circ$)</td>
<td>$Z_{\delta}$ = 50.12 $\Omega$ ($\delta = 30.58^\circ$)</td>
<td>$Z_{\delta}$ = 6.66 $\Omega$ ($\delta = 30.96^\circ$)</td>
<td>$Z_{\delta}$ = 6.66 $\Omega$ ($\delta = 30.96^\circ$)</td>
<td>$Z_{\delta}$ = 6.66 $\Omega$ ($\delta = 30.96^\circ$)</td>
</tr>
</tbody>
</table>

**Table IV** TW-SDPA Impedance and Electrical Length Design Values Obtained With the Proposed Technique

![Fig. 6. Carrier device OMN and drain biasing network synthesised at I-generator and package planes](image-url)
better wideband performance functionalities at OPBO and saturation levels. This demonstration in itself, not only indicates the acquisition of optimal impedance matching solutions at $R_1$ and $R_2$. Additionally, it also demonstrates the feasibilities of the proposed technique for bandwidth extension in the TW-SDPA. Another more important demonstration not to be overlooked, is the evidence that the impedance trajectories in $Z_{CFM1}(R1)$ and $Z_{CFM2}(R2)$ as shown in Fig. 7, are within the regions shown in Fig. 3. Therefore, supporting the proof of the design strategy.

Following the separate accomplishments of the carrier and peaking sub-amplifiers, both devices should be put together. A two-section Wilkinson power divider is then designed and positioned at their inputs to combine the carrier and peaking paths.

Finally, Fig. 8 shows the simulated drain efficiency and gain performances of the proposed TW-SDPA. In the 1.3–2.5 GHz operating frequency band, the drain efficiency is within 52.4%–75.3% at saturation and the drain efficiency at 6 dB OPBO is within 43%–55%. The output power is within 42.7–45 dBm while the gain is within 9.7–12 dB at saturation.

**Fig. 7. Load impedance trajectories of carrier device OMN and drian biasing network at (a) OPBO and (b) saturation.**

**Fig. 8. Simulated drain efficiency and gain performances of the proposed TW-SDPA.**

**Fig. 9. Proposed CFLMT design flow for TW-SDPAs.**

In summary, Fig. 9 shows the flowchart of the procedure used to design TW-SDPAs using the proposed CFLMT.

**IV. EXPERIMENTAL VERIFICATION**

For verification of the proposed design approach, a broadband TW-SDPA was fabricated on a Rogers RO4350B substrate with $\varepsilon_r = 3.66$, $h = 20$ mil and $\delta = 0.003$ as shown in Fig. 10. To evaluate the performance of the designed TW-SDPA, the measurements under continuous wave signals excitations and modulated signals were carried out as demonstrated below.
A. DPA Measurement Results With Continuous Wave Signals

The proposed TW-SDPA was stimulated by a continuous wave signal sweeping from 1.2 GHz to 2.4 GHz with a step of 0.1 GHz. The TW-SDPA operating frequency band spans from 1.2 GHz to 2.4 GHz, successfully accounting for 66.7% FBW. Fig. 11 shows the measured efficiency and gain as functions of the output power for all the frequency in the band, revealing performances in line with the expectations. Fig. 12 shows the comparison between measured and simulated drain efficiencies at 6 dB OPBO and saturation. The experimental results clearly indicate that at saturation and 6 dB OPBO, 41.59%–81.1% and 35%–63% drain efficiencies are, respectively, achieved successfully in the 1.2–2.4 GHz working band. The working band of the proposed TW-SDPA indicates 15.5%–29.7% increment in FBW when compared with the continuous mode-based TW-SDPAs reported by Chen et al. [32–34] and Shi et al. [35–36]. Fig. 13 shows the measured and simulated output power of the proposed TW-SDPA at 6 dB OPBO and saturation. At saturation, 42–45 dBm output power is achieved while at 6 dB OPBO, 35.52–39 dBm output power is recorded in measurement.

B. DPA Measurement Results With Modulated Signals

To evaluate the capability of the fabricated TW-SDPA to efficiently work in wireless communication systems, it was tested with a 20-MHz long-term evolution (LTE) modulated signal characterised by a peak-to-average power ratio (PAPR) of 8 dB. In these measurements, the modulated signal is generated by a vector signal generator while the output spectrum and adjacent channel leakage ratio (ACLR) are measured by a vector signal analyzer. Indirect learning approach is used to realise a DPD function also. In particular, a memory polynomial model with nonlinear order 4 and memory depth 13 is chosen to build the DPD structure. All the model parameters are estimated through the least square algorithm. As a proof of the effectiveness of the DPD, Fig. 14 shows the captured DPA spectra at 2.3 GHz and in correspondence of an average output power of 36.7 dBm before and after DPD. In the latter case, the ACLR is reduced from –28 dBc to –47 dBc. For completeness, Fig. 15 summarises the measured ACLR before and after DPD, the average output power (Pout) (36–37 dBm) and drain efficiency (DE) (higher than 46%) when the TW-SDPA is driven with the same modulated signal in the overall working frequency band, i.e. 1.2–2.4 GHz, step 0.1 GHz. Notably, similar levels of linearity improvements have been registered.

A summary of performance comparison of this work with some recently reported TW-SDPAs is presented in Table V. Table V suggests the efficacy of the proposed design approach and thus showing its wide FBW performance achieved with comparable results.
## Comparison with Some Recently Reported Two-Way GaN Symmetrical Doherty Power Amplifiers

<table>
<thead>
<tr>
<th>Reference</th>
<th>Frequency (GHz)</th>
<th>FBW (GHz)</th>
<th>Output Power (dBm)</th>
<th>Gain (dB)</th>
<th>$\eta_{\text{sat}}$ (%)</th>
<th>$\eta_{\text{6dB}}$ (%)</th>
<th>Proposed Technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>[29]</td>
<td>1.7–2.6</td>
<td>0.9 (42)</td>
<td>44.6–46.3</td>
<td>8.6–10.5</td>
<td>57–66</td>
<td>47–57</td>
<td>Post-Matching</td>
</tr>
<tr>
<td>[30]</td>
<td>1.5–2.5</td>
<td>1.0 (50)</td>
<td>42–44.5</td>
<td>8–11</td>
<td>55–75</td>
<td>42–53</td>
<td>Novel Combiner</td>
</tr>
<tr>
<td>[31]</td>
<td>1.5–2.4</td>
<td>0.9 (46)</td>
<td>43.1–44.4</td>
<td>Not indicated</td>
<td>57–74</td>
<td>45–56</td>
<td>Bayesian Optimisation</td>
</tr>
<tr>
<td>[32]</td>
<td>1.7–2.7</td>
<td>1.0 (45.5)</td>
<td>52.7–54.3*</td>
<td>12.3–13.7</td>
<td>53–66</td>
<td>40–50.2</td>
<td>Continuous Optimisation</td>
</tr>
<tr>
<td>[33]</td>
<td>1.65–2.75</td>
<td>1.1 (50)</td>
<td>44–46</td>
<td>7–8</td>
<td>60–75</td>
<td>50–60</td>
<td>Continuous Mode</td>
</tr>
<tr>
<td>[34]</td>
<td>1.65–2.75</td>
<td>1.1 (50)</td>
<td>44.5–46.3</td>
<td>9.3–11.7</td>
<td>60–77</td>
<td>52–66</td>
<td>Continuous Mode</td>
</tr>
<tr>
<td>[35]</td>
<td>1.6–2.7</td>
<td>1.1 (51)</td>
<td>43.8–45.2</td>
<td>9.4–11.5</td>
<td>56–75.3</td>
<td>46.5–63.5</td>
<td>Continuous Mode</td>
</tr>
<tr>
<td>[36]</td>
<td>1.65–2.4</td>
<td>0.75 (37)</td>
<td>43.5–45.1</td>
<td>11.5–12.1</td>
<td>60.1–76.2</td>
<td>46–57</td>
<td>Continuous Mode</td>
</tr>
<tr>
<td>[37]</td>
<td>1.5–2.6</td>
<td>1.1 (53.6)</td>
<td>41.8</td>
<td>&gt;9</td>
<td>40–45</td>
<td>31–35</td>
<td>Klopfenstein Taper</td>
</tr>
<tr>
<td>[40]</td>
<td>1.05–2.55</td>
<td>1.5 (83.3)</td>
<td>40–42</td>
<td>&gt;7</td>
<td>45–83</td>
<td>35–58</td>
<td>Closed-Form</td>
</tr>
<tr>
<td>[42]</td>
<td>1.1–2.4</td>
<td>1.3 (74)</td>
<td>43.3–45.4</td>
<td>9.5–11.1</td>
<td>55.4–68</td>
<td>43.8–54.9</td>
<td>Complex Combining Load</td>
</tr>
<tr>
<td>[43]</td>
<td>1.5–3.8</td>
<td>2.3 (87)</td>
<td>42.3–43.4</td>
<td>10–13.8</td>
<td>42–63</td>
<td>33–55</td>
<td>Bandwidth Estimation</td>
</tr>
</tbody>
</table>

This Work 1.2–2.4 1.2 (66.7) 42–45 7–10.52 41.59–81.1 35–63 Continuous Fuzzy Logic Mode

FBW: Fractional bandwidth. $\eta_{\text{sat}}$: Drain efficiency at saturation. $\eta_{\text{6dB}}$: Drain efficiency at 6 dB output-power-back-off level.

*: Used two 100 W GaN HEMTs CGHV40100 in design.

## V. Conclusion

This paper introduced a continuous fuzzy logic mode technique for bandwidth extension in continuous mode-based TW-SDPAs. The proposed technique uses a modelled $K$-means unsupervised learning clustering algorithm and continuous mode technique in a modelled fuzzy logic system environment. A TW-SDPA was designed and fabricated to validate the proposed theory. The experimental results with continuous wave signals excitations clearly demonstrated that the TW-SDPA achieved drain efficiencies within 41.59%–81.1% and 35%–63% at saturation and 6 dB OPBO levels, respectively, 42–45 dBm output power and 7–10.52 dB gain over a frequency range spanning from 1.2 GHz to 2.4 GHz. Correspondingly, a FBW of 66.7% was successfully achieved. Upon comparing the obtained FBW in this work to that of the reported continuous mode-based TW-SDPAs in the literature, the proposed TW-SDPA successfully achieved 15.5%–29.7% increment in FBW. Furthermore, the performance assessment under modulated signals confirmed ACLR better than -46 dBc and average drain efficiency within 46%–55% was successfully obtained. According to the recorded experimental results, it is worth mentioning that this technique showed excellent resiliency to the FBW inaccuracies of existing continuous mode-based TW-SDPAs.

## References


